International Journal of Electrical and Computer Engineering (IJECE)
Vol. 14, No. 5, October 2024, pp. 5866~5873
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i5.pp5866-5873

Detection of fungal diseases of plants from leaf images based on neural network technologies

Ievgen Fedorchenko[1], Mohd Faizal Yusof[2], Andrii Oliinyk[1], Maksym Chornobuk[1], Mykola Khokhlov[1], Jamil Abedalrahim Jamil Alsayaydeh[3]
[1]Department of Software tools, Faculty of Computer Science and Technology, Zaporizhzhia Polytechnic National University, Zaporizhzhia, Ukraine
[2]Research Section, Faculty of Resilience, Rabdan Academy, Abu Dhabi, United Arab Emirates
[3]Department of Engineering Technology, Fakulti Teknologi and Kejuruteraan Elektronik and Komputer, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia

Article Info

Article history:

Received Dec 1, 2023
Revised Jul 3, 2024
Accepted Jul 9, 2024

Keywords:

Classification
Convolutional neural network
Machine learning
Machine vision
Pattern recognition
TensorFlow

ABSTRACT

The paper addresses the issue of automating the detection of fungal diseases in plants using digital images of their leaves. The spread of diseases among agricultural and horticultural crops causes significant economic losses worldwide, making the development of an effective and affordable solution to this problem highly valuable. Literature analysis suggests the viability of employing a convolutional neural network (CNN) to tackle this issue. The 'Fungus recognition' model was developed based on a custom CNN architecture using the TensorFlow library. The model underwent training and testing on a publicly available dataset. Test results show that 'Fungus recognition' achieves a classification accuracy level of 90%, surpassing similar models considered. The developed model can be adapted for deployment on mobile computing devices, paving the way for its practical implementation in agriculture and horticulture.

Corresponding Author:

Jamil Abedalrahim Jamil Alsayaydeh
Department of Engineering Technology, Fakulti Teknologi and Kejuruteraan Elektronik and Komputer, Universiti Teknikal Malaysia Melaka
76100 Melaka, Malaysia
Email: jamil@utem.edu.my

1. INTRODUCTION

Agriculture remains an integral and vital part of the world economy. In some countries, agriculture generates a significant part of national income and jobs [1]. Approximately a quarter of the world's population is directly employed in agriculture. It is difficult to estimate the amount of labor and economic output that depends on or services agriculture [2].

One of the most important problems of agriculture around the world remains the damage caused as a result of certain plant diseases. Parasites and pests cause an average of up to 40% of crop losses in maize, potatoes, rice, soybeans and wheat worldwide. Plant diseases caused by bacteria, fungi, and viruses annually cost the world economy hundreds of billions of the United States dollars. Given the fact that approximately 10% of the Earth's population suffers from hunger, the problem of crop loss has negative consequences for the entire world [3].

Typical representatives of globally distributed parasitic organisms, in particular fungal ones that affect the dews of agricultural crops, are the so-called rust fungi and powdery mildew fungi that cause diseases of the same name. Rust fungi are a global threat to crops, in particular, wheat. Stem and stripe rusts can cause up to 100% yield losses, while wheat leaf rust can cause up to 50% losses. Powdery mildew is also one of the most serious fungal diseases in field and greenhouse cultivation of various agricultural crops, its infection can lead to serious yield losses [4], [5].

An important stage in the fight against such diseases is their timely detection. Because of this, the automatic detection of crop diseases based on artificial intelligence models, in particular deep learning, is gaining popularity, which leads to making the right decisions about control and minimizing crop loss. Such automation of plant disease detection can help reduce the amount of spent pesticides, reduce the cost of crop cultivation and promote healthy and sustainable development of agriculture.

At the moment, there are models designed to solve a similar problem, namely, to detect a number of diseases in different crops. The accuracy of those similar systems discussed below varies from 70% to about 85%. Thus, the system from work [6] allows to recognize powdery mildew with an accuracy of about 86%. In this work, attention is paid to the development of the neural network model and an automatic system for the most accurate detection of rust and powdery mildew fungi [6]–[9].

One of these models is given in article [6], where the authors use the well-known YOLOv5 convolutional neural network (CNN) architecture to detect plant damage by various diseases, including powdery mildew and anthracnose. According to the testing results, the developed model achieved classification accuracy values of 70% in general; 86.5% and 86.8% for powdery mildew and anthracnose, respectively.

Mishra *et al.* [7] proposed a system based on a convolutional neural network for detecting corn diseases based on images of the leaves of this crop. According to the test results, it reaches an accuracy of 88%, which demonstrates the potential of this method. The presented corn disease recognition model is able to work on autonomous intelligent devices such as raspberry pi or smartphones and drones.

The solution proposed in article [8] is aimed at identifying wheat diseases. The authors suggest using a model based on a two-dimensional convolutional bidirectional gated recurrent unit neural network. The authors compare the proposed model with traditional convolutional neural networks, concluding that it has a higher level of accuracy. The proposed model achieves a level of 74.3% classification accuracy.

In the article [9], the author's model based on the region-based convolutional neural network (R-CNN) is proposed. The model is aimed at detecting diseases such as brown blight, blister blight and algal leaf spot affecting tea. The model detects diseases based on leaf images, with an average classification accuracy of 69.79%.

Mukherjee *et al.* [10] study the possibility of detecting 4 types of apple tree diseases by images of leaves. The authors used the well-known GoogLeNet model. During training, the model achieved a classification accuracy of 85.04%.

As can be seen from the papers discussed above, a typical system for solving such a problem provides an accuracy of 70-85%. Given the enormous importance of agriculture in general and the huge potential losses due to plant damage not detected in time, it is appropriate to develop a system with greater accuracy. The creation of the author's architecture based on the basics of a convolutional neural network is described below. The proposed model is capable of solving the problem with a classification accuracy of about 90%. A comparison between the accuracy of the proposed model and the accuracy of the models discussed above will also be demonstrated below.

2. THE PROPOSED METHOD FOR DETECTION OF FUNGAL DISEASES OF PLANTS FROM LEAF IMAGES BASED ON NEURAL NETWORKS

A model and its software implementation of the system for automatic detection of fungal diseases of plants based on images of leaves was developed. The system consists of two components: a machine learning model based on a convolutional neural network and a user interface. The problems of preliminary processing of input data, development of model architecture, testing of its quality are considered.

All images from the dataset [11] have already been reduced to the same size -4,000 by 2,672 pixels. However, building a neural network capable of processing images of such dimensions would require an unattainable amount of resources under the conditions of the development of this project. To solve this problem, all images from the dataset were reduced to a smaller size-500 by 250 pixels. In the future, all images entering the model input will be scaled to this dimension using the *load_img* function from the Keras library. An example of an image from the dataset [11], which has already been reduced to the given dimension, is shown in Figure 1.

Since the model solves the problem of multinominal classification, that is, it determines whether the given image belongs to one of three classes: healthy, plant affected by powdery mildew, plant affected by rust, it is natural to use a cost function called categorical cross-entropy. This function can be used when the output attribute of each instance represents one of several categories [12]–[22]. At the same time, the machine learning model should output the probability of the ratio of the current instance to each of the classes. Categorical cross-entropy indicates high classification accuracy when the probabilities determined by the model are maximally correlated with the real class to which the instance belongs [22]–[34]. The function is defined as (1):

$$L = -\sum_{i=1}^{N} y_i * \log p_i, \quad (1)$$

where y_i is the real value, p_i is the value predicted by the model, N is the number of classes.

Figure 1. Processed image from [11]

The basis of the developed system, a machine learning model for detecting plant damage by fungal diseases, is based on a multi-layer convolutional neural network of the author's architecture. This architecture received the conventional name “Fungus recognition”. Visually, the architecture of “Fungus recognition” is shown in Figure 2. It consists of an input layer that accepts color images with a size of 500 by 250 pixels; five pairs of convolutional and aggregation layers; one dropout layer; three fully connected layers; one output layer with the softmax activation function.

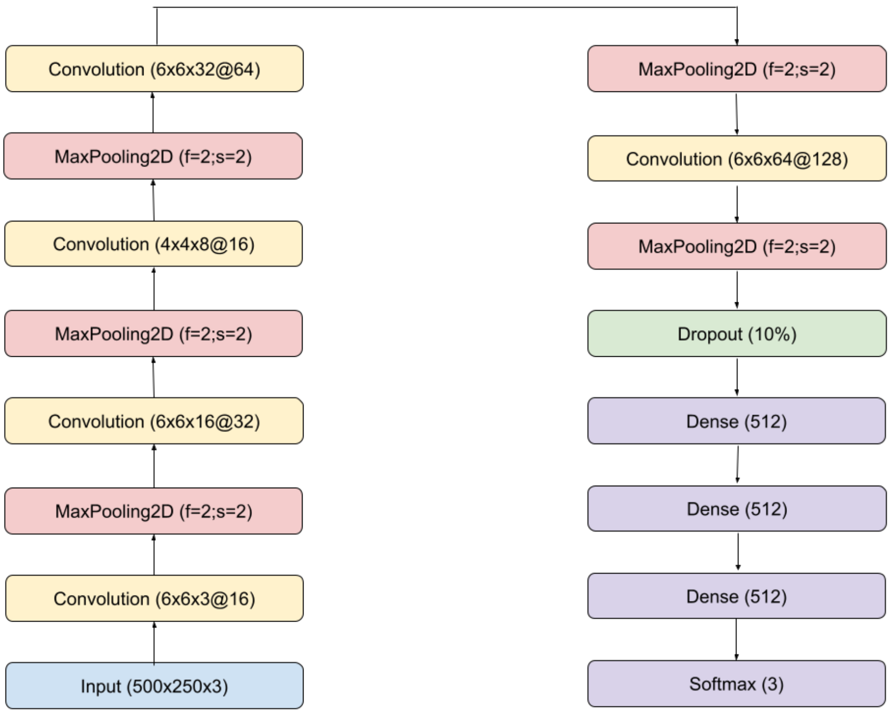
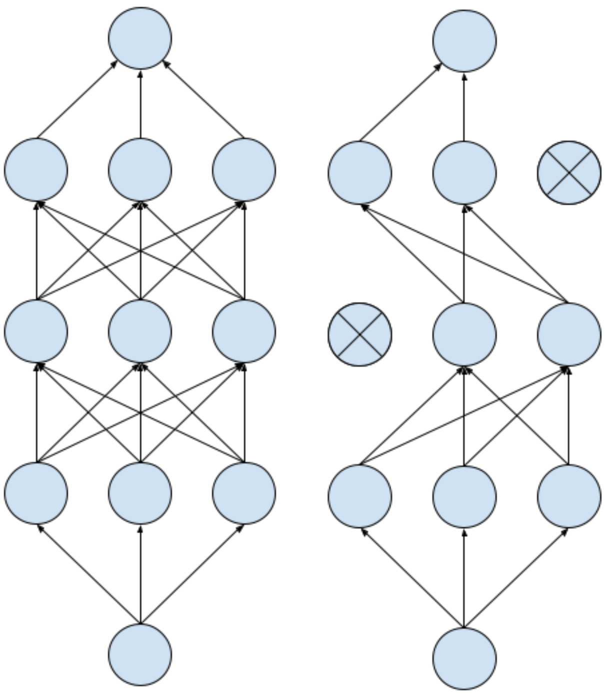


Figure 2. “Fungus recognition” architecture. Input: input layer, Convolution: convolutional layers, MaxPooling2D: aggregation layers, Dropoup: dropout layer, Dense and Softmax: fully connected layers

In the developed neural network architecture, convolutional and aggregation pairs are used. Convolutional layers are used to find patterns in input data, and aggregation layers are used to reduce the dimensionality of data and extract useful information. The number and size of convolutional and aggregation layers used in "Fungus recognition" corresponds to the specifics of a specific task. As a rule, it is impossible to immediately identify the best configuration of such layers, and their effective adjustment is possible only as a result of a series of tests. In terms of the given task, it was empirically established that these settings lead to optimal results, i.e., to high values of the recognition accuracy of the "Fungus recognition" model.

Adding a dropout layer in the proposed neural network architecture is used to solve the retraining problem. The parameter for this type of layer is the percentage of neurons that will be set to zero during each training epoch of the network. The value of 10% used in Fungus recognition was chosen empirically. It made it possible to achieve the best accuracy rates during model training. Schematic application of the method of reducing redundant neuroelements using dropout layers is shown in Figures 3(a) and 3(b).



(a) (b)

Figure 3. Graphical interpretation of the application of the method of reducing redundant neuroelements using dropout layers, (a) before their application, and (b) after their application)

Using an output layer that consists of a number of neurons equal to the number of classes to which the instances can belong and has a softmax activation function is a typical solution for multinomial classification models. This layer is used to transform a vector of real numbers into a probability distribution, where each element of the vector represents the probability that the input instance belongs to a certain class. From a mathematical point of view, the softmax function takes as input a vector of real numbers and returns a vector of probabilities. Softmax is defined as (2):

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{k=1}^{K} e^{z_k}}, \tag{2}$$

where z_i is the i-th value of the input vector.

Thus, in order to solve the problem of detection of plant lesions caused by fungal diseases, which is reduced to the formal problem of multinominal classification of digital color images, the "Fungus recognition" model was built based on a convolutional neural network. The model uses convolutional layers for finding patterns in input data, aggregation layers are used to reduce the dimensionality of data and extract useful information, and output layer based on softmax activation function and categorical cross-entropy cost function. A dropout layer was used to reduce the overfitting effect.

The “Fungus recognition” model was trained during 12 training epochs. The dataset [11] was used for training, the pre-processing of data from which is described above. The dataset contains 1,530 images divided into three classes: healthy plants, rust fungus damage, and powdery mildew fungus damage. The images are also divided into three sets: training, validation and test. The model was trained using the training set and validated using the validation set. The training results, including data on the value of the loss function and classification accuracy for each of the epochs, are shown in Figure 4. The data are also summarized in Table 1. After training, the model was saved and tested on a test set of data from the dataset [11]. The test results are as follows: the value of the loss function is 0.3608, the classification accuracy is more than 90%.

Figure 4. Visualization of data on “Fungus recognition” training

Table 1. Data on the results of the “Fungus recognition” training

Epoch	The value of the loss function	Classification accuracy values on the validation data set
1	1.1261	45.0%
2	0.6928	66.7%
3	0.6801	68.3%
4	0.4967	81.7%
5	0.5796	76.7%
6	0.5110	85.0%
7	0.5006	83.3%
8	0.5444	83.3%
9	0.4659	85.0%
10	0.3007	93.3%
11	0.4132	80.0%
12	0.2084	91.7%

3. RESULTS AND DISCUSSIONS

This paper considers the development of a model for automatic detection of fungal diseases in plants using digital images of their leaves that is capable of achieving a classification accuracy of 90% or higher. Existing similar models have recognition accuracy in the average range of 70-85%. Increasing the level of recognition accuracy is important for better practical use of the model in agriculture.

The proposed model is based on “Fungus recognition” architecture based on convolutional neural network. The model utilizes known techniques to reduce the effect of overtraining. Thus, the developed model achieves a classification accuracy of more than 90% based on the results of 12 training epochs.

Table 2 summarizes information about the developed model “Fungus recognition”, as well as models from the literature that solve similar problems. “Fungus recognition” is ahead of other models in classification accuracy, while being able to distinguish between healthy plants, plants affected by rust fungi and plants affected by powdery mildew fungi. The developed model is also quite simple, namely, it consists of only five pairs of convolutional and aggregation layers and 4 fully connected layers. This allows instant classification results on modern portable computing devices, making the model practically useful.

The used dataset contains only 1,530 images divided into 3 classes, which significantly limits the model training capabilities. It is known that one of the most effective ways to improve model accuracy and reduce the effect of overtraining is to increase the training sample of data. To further improve the results of the “Fungus recognition” architecture, the best strategy would be to create a model based on a new dataset, with a number of samples that significantly exceeds the size of the current dataset.

Table 2. Comparison of “Fungus recognition” with similar models

Model	The method used	Classification accuracy
Fungus recognition	CNN	90%
Corn plant disease recognition [7]	NN	88%
GoogleNet [10]	CNN	85%
2D-CNN-BidGRU [8]	Bidirectional RNN	74%
YOLOv5 [6]	CNN	70%
Faster R-CNN [9]	R-CNN	70%

4. CONCLUSIONS

The problem of detection of plant damage by fungal diseases was considered. Machine learning models that solve similar problems were analyzed. It was concluded that it is appropriate to develop a model for detecting plant damage by fungal diseases based on a convolutional neural network.

The “Fungus recognition” model was developed, which consists of an input layer accepting color images of 500 by 250 pixels, five pairs of convolutional and aggregation layers, one dropout layer, three fully connected layers, and one output layer with softmax activation function. The developed model was trained and tested on a publicly available dataset. The model showed a classification accuracy level of 90% on the test data set. According to this indicator, it was ahead of the similar solutions discussed above, which justifies its innovativeness and feasibility of use in practice.

ACKNOWLEDGMENTS

The authors extend their appreciation to Universiti Teknikal Malaysia Melaka (UTeM) and to the Ministry of Higher Education of Malaysia (MOHE) for their support in this research.

REFERENCES

[1] J. M. Alston and P. G. Pardey, “Agriculture in the global economy,” *Journal of Economic Perspectives*, vol. 28, no. 1, pp. 121–146, Feb. 2014, doi: 10.1257/jep.28.1.121.
[2] B. Dedieu and S. Schiavi, “Insights on work in agriculture,” *Agronomy for Sustainable Development*, vol. 39, no. 6, Dec. 2019, doi: 10.1007/s13593-019-0601-3.
[3] S. He and K. M. Creasey Krainer, “Pandemics of people and plants: which is the greater threat to food security?,” *Molecular Plant*, vol. 13, no. 7, pp. 933–934, Jul. 2020, doi: 10.1016/j.molp.2020.06.007.
[4] P. Prasad, S. Chander Bhardwaj, O. Prakash Gangwar, and S. Kumar, “Wheat rust research: Impact, thrusts, and roadmap to sustained wheat production,” in *Improving Cereal Productivity through Climate Smart Practices*, Elsevier, 2020, pp. 177–203.
[5] L. Manjunatha, S. Singh, B. M. Ravikumara, G. Narasa Reddy, and M. Senthilkumar, “Ampelomyces,” in *Beneficial Microbes in Agro-Ecology: Bacteria and Fungi*, Elsevier, 2020, pp. 833–860.
[6] Z. Chen *et al.*, “Plant disease recognition model based on improved YOLOv5,” *Agronomy*, vol. 12, no. 2, 2022, doi: 10.3390/agronomy12020365.
[7] S. Mishra, R. Sachan, and D. Rajpal, “Deep convolutional neural network based detection system for real-time corn plant disease recognition,” *Procedia Computer Science*, vol. 167, pp. 2003–2010, 2020, doi: 10.1016/j.procs.2020.03.236.
[8] X. Jin, L. Jie, S. Wang, H. J. Qi, and S. W. Li, “Classifying wheat hyperspectral pixels of healthy heads and fusarium head blight disease using a deep neural network in the wild field,” *Remote Sensing*, vol. 10, no. 3, Mar. 2018, doi: 10.3390/rs10030395.
[9] S. H. Lee, C. C. Wu, and S. F. Chen, “Development of image recognition and classification algorithm for tea leaf diseases using convolutional neural network,” 2018, doi: 10.13031/aim.201801254.
[10] S. Mukherjee, P. Kumar, R. Saini, “Plant disease identification using deep neural networks,” *Journal of Multimedia Information System (JMIS)*, vol. 4, no. 4, pp. 233–238, 2017, doi: 10.9717/JMIS.2017.4.4.233.
[11] R. Rahman, “Plant disease recognition dataset,” *Kaggle*. https://www.kaggle.com/datasets/rashikrahmanpritom/plant-disease-recognition-dataset/data (accessed Nov. 08, 2023).
[12] Q. Wang, Y. Ma, K. Zhao, and Y. Tian, “A comprehensive survey of loss functions in machine learning,” *Annals of Data Science*, vol. 9, no. 2, pp. 187–212, Apr. 2022, doi: 10.1007/s40745-020-00253-5.

[13] I. Fedorchenko, A. Oliinyk, A. Stepanenko, T. Zaiko, S. Shylo, and A. Svyrydenko, “Development of the modified methods to train a neural network to solve the task on recognition of road users,” *Eastern-European Journal of Enterprise Technologies*, vol. 2, no. 9–98, pp. 46–55, Apr. 2019, doi: 10.15587/1729-4061.2019.164789.
[14] A. Mujumdar and V. Vaidehi, “Diabetes prediction using machine learning algorithms,” *Procedia Computer Science*, vol. 165, pp. 292–299, 2019, doi: 10.1016/j.procs.2020.01.047.
[15] I. Fedorchenko, A. Oliinyk, A. Stepanenko, T. Zaiko, S. Korniienko, and N. Burtsev, “Development of a genetic algorithm for placing power supply sources in a distributed electric network,” *Eastern-European Journal of Enterprise Technologies*, vol. 5, no. 3–101, pp. 6–16, Oct. 2019, doi: 10.15587/1729-4061.2019.180897.
[16] J. A. J. Alsayaydeh *et al.*, “Development of vehicle door security using smart tag and fingerprint system,” *International Journal of Engineering and Advanced Technology*, vol. 9, no. 1, pp. 3108–3114, Oct. 2019, doi: 10.35940/ijeat.E7468.109119.
[17] I. Fedorchenko, A. Oliinyk, J. A. J. Alsayaydeh, A. Kharchenko, A. Stepanenko, and V. Shkarupylo, “Modified genetic algorithm to determine the location of the distribution power supply networks in the city,” *ARPN Journal of Engineering and Applied Sciences*, vol. 15, no. 23, pp. 2850–2867, 2020.
[18] F. A. Phang *et al.*, “Integrating drone technology in service learning for engineering students,” *International Journal of Emerging Technologies in Learning*, vol. 16, no. 15, pp. 78–90, Aug. 2021, doi: 10.3991/ijet.v16i15.23673.
[19] V. Meshram, K. Patil, V. Meshram, D. Hanchate, and S. D. Ramkteke, “Machine learning in agriculture domain: a state-of-art survey,” *Artificial Intelligence in the Life Sciences*, vol. 1, Dec. 2021, doi: 10.1016/j.ailsci.2021.100010.
[20] A. K. M. Zakir Hossain, N. Bin Hassim, J. A. J. Alsayaydeh, M. K. Hasan, and M. R. Islam, “A tree-profile shape ultra wide band antenna for chipless RFID tags,” *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 4, pp. 546–550, 2021, doi: 10.14569/IJACSA.2021.0120469.
[21] J. Lidwell-Durnin and A. Lapthorn, “The threat to global food security from wheat rust: ethical and historical issues in fighting crop diseases and preserving genetic diversity,” *Global Food Security*, vol. 26, Sep. 2020, doi: 10.1016/j.gfs.2020.100446.
[22] K. Gromaszek, M. M. Bykov, V. V. Kovtun, A. Raimy, and S. Smailova, “Neural network modelling by rank configurations,” in *Photonics Applications in Astronomy, Communications, Industry, and High-Energy Physics Experiments 2018*, Oct. 2018, doi: 10.1117/12.2501521.
[23] P. S. Abdul Lateef Haroon and U. Eranna, “A simplified machine learning approach for recognizing human activity,” *International Journal of Electrical and Computer Engineering*, vol. 9, no. 5, pp. 3465–3473, Oct. 2019, doi: 10.11591/ijece.v9i5.pp3465-3473.
[24] L. Elhaloui, S. El Filali, E. H. Benlahmer, M. Tabaa, Y. Tace, and N. Rida, “Machine learning for internet of things classification using network traffic parameters,” *International Journal of Electrical and Computer Engineering*, vol. 13, no. 3, pp. 3449–3463, Jun. 2023, doi: 10.11591/ijece.v13i3.pp3449-3463.
[25] S. A. Ebiaredoh-Mienye, E. Esenogho, and T. G. Swart, “Artificial neural network technique for improving prediction of credit card default: A stacked sparse autoencoder approach,” *International Journal of Electrical and Computer Engineering*, vol. 11, no. 5, pp. 4392–4402, Oct. 2021, doi: 10.11591/ijece.v11i5.pp4392-4402.
[26] O. Bisikalo, O. Danylchuk, V. Kovtun, O. Kovtun, O. Nikitenko, and V. Vysotska, “Modeling of operation of information system for critical use in the conditions of influence of a complex certain negative factor,” *International Journal of Control, Automation and Systems*, vol. 20, no. 6, pp. 1904–1913, Apr. 2022, doi: 10.1007/s12555-021-0368-6.
[27] S. Krishnan, P. Magalingam, and R. Ibrahim, “Hybrid deep learning model using recurrent neural network and gated recurrent unit for heart disease prediction,” *International Journal of Electrical and Computer Engineering*, vol. 11, no. 6, pp. 5467–5476, Dec. 2021, doi: 10.11591/ijece.v11i6.pp5467-5476.
[28] R. Saifan and F. Jubair, “Six skin diseases classification using deep convolutional neural network,” *International Journal of Electrical and Computer Engineering*, vol. 12, no. 3, pp. 3072–3082, Jun. 2022, doi: 10.11591/ijece.v12i3.pp3072-3082.
[29] D. Verma, C. Bose, N. Tufchi, K. Pant, V. Tripathi, and A. Thapliyal, “An efficient framework for identification of tuberculosis and pneumonia in chest X-ray images using neural network,” *Procedia Computer Science*, vol. 171, pp. 217–224, 2020, doi: 10.1016/j.procs.2020.04.023.
[30] Electricalvoice, “Genetic algorithm – advantages and disadvantages,” *Electricalvoice*, 2017. https://electricalvoice.com/genetic-algorithm-advantages-disadvantages/ (accessed Nov. 30, 2023).
[31] V. A. Sairam, “spine fracture prediction from C.T.,” Kaggle https://www.kaggle.com/datasets/vuppalaadithyasairam/spine-fracture-prediction-from-xrays (accessed Nov. 30, 2023).
[32] V. Kovtun, M. Bykov, T. Gryshchuk, and O. Bykova, “Theoretical and experimental investigation of error detecting and error correcting ability of rank codes,” *CEUR Workshop Proceedings*, vol. 3668, pp. 35–47, 2024.
[33] H. B. Wong and G. H. Lim, “Measures of diagnostic accuracy: sensitivity, specificity, PPV and NPV,” in *Proceedings of Singapore Healthcare*, vol. 20, no. 4, pp. 316–318, Dec. 2011, doi: 10.1177/201010581102000411.
[34] B. Abuhaija *et al.*, “A comprehensive study of machine learning for predicting cardiovascular disease using WEKA and SPSS tools,” *International Journal of Electrical and Computer Engineering*, vol. 13, no. 2, pp. 1891–1902, Apr. 2023, doi: 10.11591/ijece.v13i2.pp1891-1902.

BIOGRAPHIES OF AUTHORS

Ievgen Fedorchenko current appointment is as senior lecturer of Software Tools Department of National University “Zaporizhzhia Polytechnic”. He holds a specialist (2000) with a specialization in production of electronic devices, bachelor (2012) and master (2013) degree in software engineering from Zaporizhzhia National Technical University, Ukraine. Author/co-author of 50+ research publications cited in over 100 documents. Research interests include artificial intelligence, big data, neural networks, computer vision, and soft computing. He can be contacted at email: evg.fedorchenko@gmail.com.

Mohd Faizal Yusof current appointment is as associate researcher - lecturer at Rabdan Academy, UAE. He holds a Bachelor of Science in electrical engineering from Northwestern University (1998) and MBA in technology entrepreneurship from Universiti Teknologi Malaysia (2008). He is an experienced blockchain researcher, university technology transfers officer, software developer, and former start-ups entrepreneur. His research interests include design science research, blockchain, cryptocurrency, artificial intelligence and social entrepreneurship. He can be contacted at email: myusof@ra.ac.ae.

Andrii Oliinyk current appointment is as Doctor of Science, professor of software tools Department of National University "Zaporizhzhia Polytechnic". Received master's degree in software engineering (2007) from Zaporizhzhia National Technical University, Ukraine. He has a Ph.D. degree on artificial intelligence (2009). He is Doctor of Science on artificial intelligence, professor (2021). Author/co-author of 100+ research publications cited in over 300 documents. Research interests include artificial intelligence, big data, neural networks, computer vision, and soft computing. Actively supervises Ph.D. students, reviews reputable journals, secures grants. He can be contacted at email: olejnikaa@gmail.com.

Maksym Chornobuk is a student at National University "Zaporizhzhia Polytechnic", Ukraine. In 2020, he completed the private complex of continuous lighting "School Eidos". Having taken part in Olympiads in computer science, mathematics and geography. After completing school, he enrolled at National University "Zaporizhzhia Polytechnic" in the specialty "computer science". Having taken part in the competition for gifted young people in the field of "physical and mathematical sciences" she has got an award of Zaporizhzhia Region Administration. His research interests include machine learning, neural networks, machine vision, and big data. He can be contacted at email: chornobuk.maksym@gmail.com.

Mykola Khokhlov received a specialist (1999) and Master of Science degree (2000). Degree in computer systems and networks, Zaporozhye National Technical University, Ukraine. Currently he is a senior lecturer at Computer Systems and Networks Department of National University "Zaporizhzhia Polytechnic" and entrepreneur in the development of microservice architectures. His research interests include artificial intelligence, modeling, and diagnostics. Actively supervises students and reviews student work. He can be contacted at email: khokhlov@zp.edu.ua.

Jamil Abedalrahim Jamil Alsayaydeh received an M.S. degree in computer systems and networks from Zaporizhzhia National Technical University, Ukraine, in 2010 and Ph.D. in engineering sciences with a specialization in automation of control processes from National Mining University, Ukraine, in 2014. Currently a senior lecturer at Universiti Teknikal Malaysia Melaka (UTeM) since 2015. Research interests include artificial intelligence, IoT, energy conservation, web service composition, and wireless mesh networks. Author/co-author of 50+ research publications cited in over 100 documents. Actively supervises students, reviews for reputable journals, secures grants, and holds membership in Board of Engineers Malaysia (BEM). He can be contacted at email: jamil@utem.edu.my.