Intelligent information systems

UDC 004.032.26:004.85+528.854 DOI: https://doi.org/10.20998/2522-9052.2021.3.13

Andrii Podorozhniak[1], Nataliia Liubchenko[1], Mykyta Kvochka[1], Ivan Suarez[2]

[1] National Technical University "Kharkiv Polytechnic Institute", Kharkiv, Ukraine
[2] Universidad Autonoma Metropolitana (Azcapotzalco), Mexico City, Mexico

USAGE OF INTELLIGENT METHODS FOR MULTISPECTRAL DATA PROCESSING IN THE FIELD OF ENVIRONMENTAL MONITORING

Abstract. **The subject** of study in the article is artificial intelligence methods that can be used for recognition of specific areas of the earth's surface in multispectral images provided by Earth remote sensing systems (ERS). **The goal** is to automate data analysis for recognizing areas affected by fire on multispectral remote sensing images. **The task** is to study and formulate a method for processing multispectral data, which makes it possible to automate the process of operational recognition of areas of burned-out areas in images, for the development of an eco-monitoring software system using artificial intelligence tools such as deep learning and neural networks. As a result of the analysis of modern methods of processing multispectral data, an investigation of the supervised learning strategy was chosen. The choice of the described method for solving an applied problem is based on the high flexibility of these method, as well as, provided that there is a sufficient amount of used training input data and correct training strategies, the possibility of analyzing heterogeneous multispectral data with ensuring high accuracy of results for each individual sample. **Conclusions**: the application of methodologies for intelligent processing of multispectral images has been investigated and substantiated. The theoretical foundations of the construction of neural networks are considered, the applied area of application is selected. An architectural model of a software product is analyzed and proposed, taking into account its scalability, the model of software system is developed and the results of its work are shown. The obtained results show the efficiency of proposed system and prospects of the proposed algorithms, which is a reason for further research and improvement of the used algorithms, with their possible use in industrial and enterprise eco-monitoring systems.

Keywords: eco-monitoring system; Earth remote sensing; multispectral image; image processing; neural network.

Introduction

Nowadays, computer systems have become so widespread that it is even difficult to name an industry that would not be affected by the process of total computerization. Every day, millions of hardware and software solutions allow humanity to solve a large number of applications precisely due to the rapid development of the information technology industry. One of such areas is undoubtedly the field of environmental monitoring. Every year the violation of state environmental standards leads to multimillion losses of the budget of our country, so government agencies and enterprises in the field of eco-monitoring aim to control, detect and prevent environmental violations. However, in order to increase the level of efficiency and manufacturability of this process it is required to use an appropriate software solutions that would facilitate the implementation of this task [1].

One of the sub-tasks in the field of environmental monitoring is the detection and control of burnt areas due to fires caused by burning grass, deadwood, etc [1, 2]. This applied task requires prompt detection of foci of environmental violations, as well as accurate identification of the affected areas in order to understand the strategy of counteraction and neutralization of the results of arson. One way to solve this problem is to use multispectral data from remote sensing systems [3]. This method allows you to cover a large amount of territory, and also allows you to achieve more effective results of the analysis due to the specifics of the burned areas detection. However, it is not possible to productively perform analysis of multispectral images by visual method, in addition, the amount of remote sensing data reach significant volumes. For these reasons, there is a need to develop an automated algorithm for analyzing such data [4].

To solve this problem, the use of modern computerized methods of multispectral images analysis in combination with machine learning tools, such as neural networks, may be proposed [5].

Problem analysis and task statement

By definition, multispectral images are images that cover visual data in certain wavelength ranges in the electromagnetic spectrum. Wavelengths can be separated by filters or detected by devices sensitive to specific wavelengths, including light from frequencies outside the visible light range, ie infrared and ultraviolet. A multispectral image typically contains two aspects of data: spatial data that transmits location information, and spectral data that transmits the reflection level of different bands. In particular, each multispectral pixel is an h-dimensional vector, where h is the number of spectral bands, the pixel is usually considered as an input sample for multispectral classification programs. Fig. 1 shows a data model of a multispectral image [6].

The effect of fire on vegetation is not binary (not only divided by "burned"/"unburned"), but rather depends on a number of conditions, such as the type of fire, its nature and the time between extinguishing the fire and obtaining an image of the burned territory. An important factor is that the reflectance of the surface, its temperature and backscattering should be taken into account, as they can be very different for the periods before and after the fire. Mapping of burnt plots of land has traditionally been done from field sketches. However, with the launch of the Earth's first artificial satellites, remote sensing has quickly become a more practical alternative for detecting burned areas, as it provides timely regional and global coverage of fires that occur in a number of areas [2, 7].

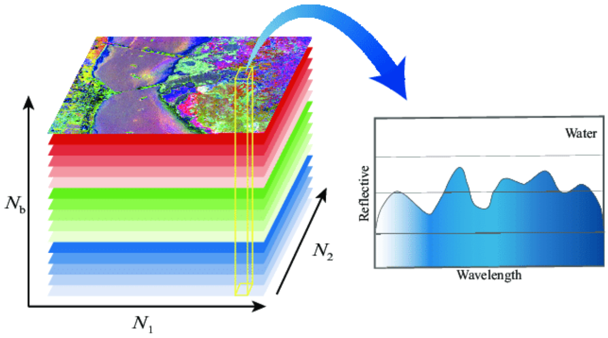

Fig. 1. Data model of a multispectral image

After all, the actual multispectral images are only input data to solve the problem of environmental monitoring and require automated analysis. Based on this, there is a question of investigating the possibility to develop an intelligent system that could process the input data of multispectral imaging and provide output data, which could allow recognizing of certain areas affected by fires with the defined probability. Since the applied problem of ecomonitoring, and the determination of burned areas in particular, are based on large data sets that require processing and automatic classification, such a problem can theoretically be solved using machine learning technologies [8].

Thus, the task of the article is to study and formulate a model of intellectual analysis of multispectral data, which will automate the recognition of burned areas for the field of environmental monitoring using artificial intelligence methods [9].

Main part

Nowadays, machine learning technologies have made a rapid leap forward in their development and spread. They have an extremely wide range of areas of practical application due to their versatility, including the field of multispectral data analysis [10].

One of the proposed methods for solving the applied problem of burned areas identification is the data mining approach for mapping. According to the study of this methodology, the NN and SVM approaches showed worse results than C5.0 or RF, due to the imbalance of the database, which led to the production of structures and models that had a low ability to generalize. Tree-based algorithms have shown better efficiency, given the ability to work with large and unbalanced databases, as well as their ability to provide accurate probabilities.

Another approach is to use the BA-Net model to identify burned areas. Traditionally, the procedure of displaying burned areas with the usage of satellite images consists of carefully crafted algorithms. Figure 2 shows an image of a burned obtained from Sentinel-2 satellites [11]. The image on the left is similar to a normal photo showing RGB colors. The image on the right contains a NIR spectrum instead of a green channel. The dark area on the right image identifies the burned area. The basic approach to displaying recorded pixels can be as simple as defining a threshold value to indicate how dark the pixels must be to display them as burned.

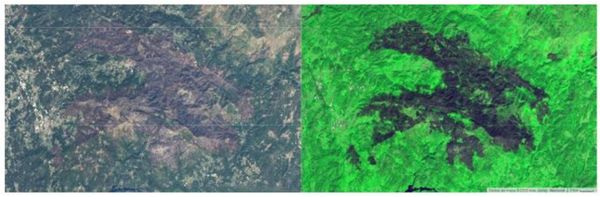

Fig. 2. Image of a burned area from the Sentinel-2 satellite

For mapping burned areas, existing products based on traditional methods can provide fairly good accuracy. However, these products are usually more accurate spatially than timely - the assignment of the burning day is often spatially inappropriate, especially if the images are contaminated with clouds, which complicate the task for any algorithm. For the BA-Net method, the following is proposed: instead of trying to write a complex algorithm to determine which pixels correspond to the burned area, the approach defines a model with several million learning parameters with architecture capable of studying spatial and time structures in image sequences. The model then looks at the images and targets and tries to make the output as close as possible to the target. This model is a set of differentiated operations, including the process of convolution in space and time, layers of reduction and scaling and the level of LSTM (class of recurrent neural networks) to capture longer time relationships in the data [12].

In mathematics, convolution is a mathematical operation on two functions (f and g) that produces a third function that expresses how the shape of one is modified by the other [13, 14]:

$$(f \times g)(t) = \int f(t-r)\, g(r)\, dr. \qquad (1)$$

LSTM, like most RNNs, is universal in the sense that with a sufficient number of network nodes, it can compute anything that a conventional computer can compute, provided it has a proper weight matrix. Traditional LSTM can be expressed by the following set of formulas:

$$\begin{aligned} f_t &= \sigma_g\left(W_f x_t + U_f h_{t-1} + b_f\right); \\ i_t &= \sigma_g\left(W_i x_t + U_i h_{t-1} + b_i\right); \\ o_t &= \sigma_g\left(W_o x_t + U_o h_{t-1} + b_o\right); \\ c_t &= f_t \circ c_{t-1} + i_t \circ \sigma_c\left(W_c x_t + U_c h_{t-1} + b_c\right); \\ h_t &= o_t \circ \sigma_h\left(c_t\right), \end{aligned} \qquad (2)$$

where x_t – input vector; h_t – hidden state vector also known as output vector; c_t – cell state vector; W, U, b – weight matrices and bias vector parameters which need to be learned during training; f_t – forget gate's activation vector; i_t, – input/update gate's activation vector; o_t – output gate's activation vector; σ_g – sigmoid function; σ_c – hyperbolic tangent function; σ_h – hyperbolic tangent function, or, as the peephole LSTM paper suggests $\sigma_h(x) = x$.

Fig. 3 shows the structure of the described model:

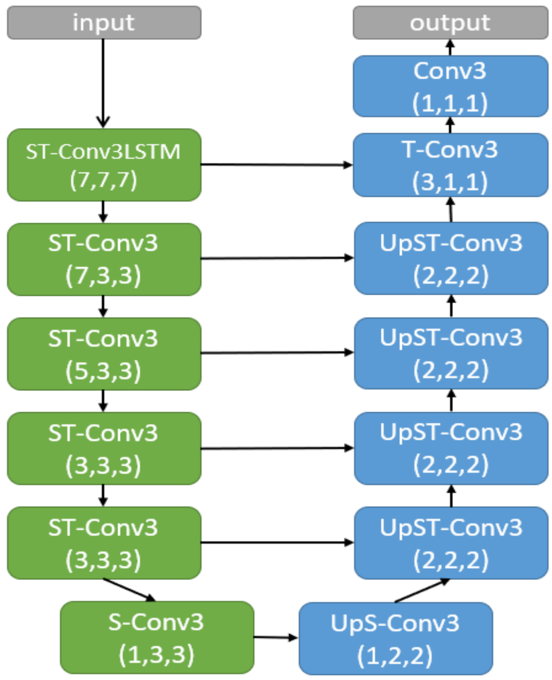

Fig. 3. The structure of the BA-Net model [15]

Consider the learning process of this model of artificial intelligence. The BA-Net input is provided with a set of 64 consecutive images for 128x128 pixels. A sequence of the same size is then generated, indicating the probability that each individual pixel corresponds to a burned area. This model uses binary cross entropy. The model parameters are then updated slightly based on gradients to move in a direction that reduces losses (i.e. increases the similarity between the output and the target). This process is repeated using a diverse set of input samples that allow models to study the spectral sign of fire in space-time data.

The diagram representing the learning process of the model is shown in Fig. 4 [11].

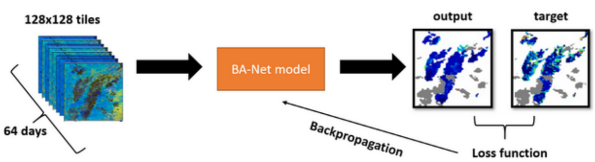

Fig. 4. Semantic diagram of BA-Net model learning

Finally, a teacher-based learning approach based on the BA-Net method was formulated and investigated. The first step to creating a classifier in the proposed model is to teach it using a training set for which the data are marked with labels (in this case it is a classification) or directly related to the value (in this case it is a regression) [16]. The algorithm tries to build a model that connects functions for a label or value. This training kit provides a model that can be used to predict new data for which there are function values but no label or ready-made output [17].

Fig. 5 shows a generalized diagram of how the proposed controlled learning process of the ML model works.

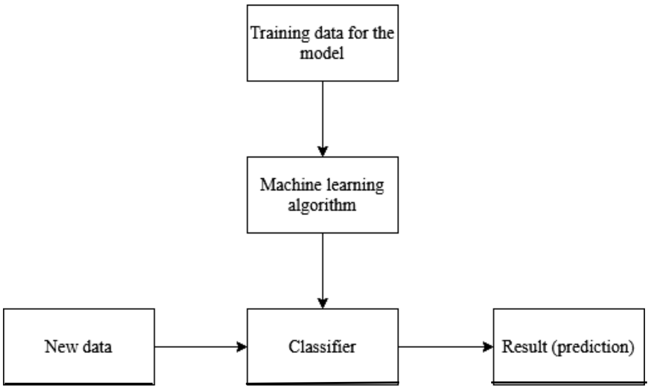

Fig. 5. Scheme of ML model teaching

The data of the consequences of the fire that occurred on August 3-9, 2018 in the Algarve, in the south of Portugal, were used as training datasets. This is a relatively easy case to analyze, as there are almost no clouds in the input images. This dataset was chosen because of the high quality of inputs and sufficient volume for full training on a given strategy. As a training sample, a set of training images with a size of 32 × 32 pixels was formed using 5 (Near Infrared) and 7 (SWIR 2) spectra of Landsat 8, for which their content is known. The total sample size is at least 8000 images, of which 1500 images contain fragments of burned areas [18].

Acer PC based on Intel Core i5 CPU with a clock speed of 2.7 GHz, Nvidia GTX 950M graphics processor and 16 GB of RAM was used to train the ML model. After the process of learning the model of artificial intelligence, the general architectural design of the developed software application was carried out. A generalized diagram of the application architecture is shown in Fig. 6.

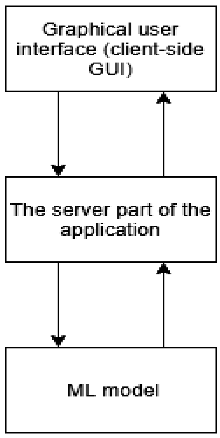

Fig. 6. Simplified diagram
of the functional components of the software product

During the development of a system based on this architecture, both the client and server part will be located on the same workstation for ease of building a working prototype. However, this architecture also has the potential to expand: for example, the system can be further modified to perform the server part and the ML model data analysis on a separate powerful workstation (local server), and users (clients) will be able to join it, for example, via TCP/IP socket [19].

The general algorithm of the typical scenario of the developed ecomonitoring system usage is shown on the sequence diagram from Fig. 7.

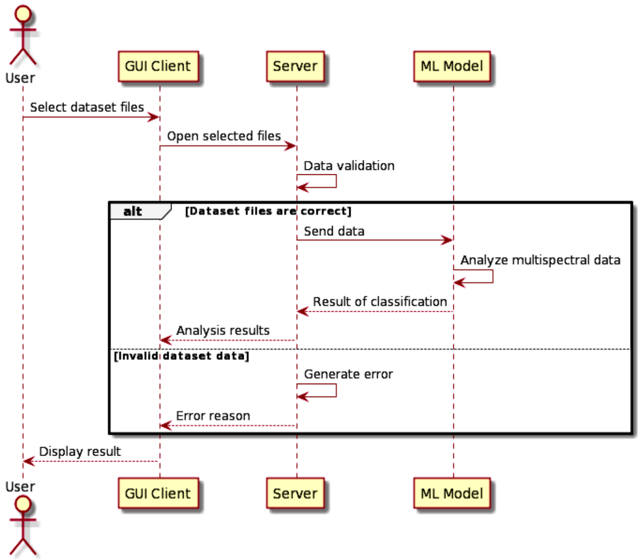

Fig. 7. Ecomonitoring system use case scenario

As can be seen from the diagram, the main action of the user is to provide a dataset, which will be further analyzed. The graphical interface is responsible for the primary reception of user input data (path to the dataset directory in the file system) and to output the result of data processing or notify error message. Server side of the application is responsible for the validation of the data provided by the user, transfering this data to the ML model and an error generation in case of invalid data. The task of the ML model is to actually analyze the provided dataset for the presence of burned areas on the provided multispectral images, as well as to send the processing results to the server part of the application.

The Python programming language and the Tkinter graphics library were chosen to implement a software product that demonstrates the proposed intelligent processing method. Of the libraries that were used to process multispectral data to build the ML model, it is worth noting the libraries Tensorflow, numpy, matplotlib, rasterio, geopandas and earthpy [20].

As a result of the development of the ecomonitoring system, a window application with a graphical interface, shown in Fig. 8, was created.

The result of data processing is presented in the form of a map indicating the probability of fire by each part of the territory, which was accessible from the input multispectral data. The value of the probability of fire damage is reflected by color: from green ("no fire damage") to dark red ("serious fire damage"). This method of data visualization is intuitive, although it is possible to make suggestions for adding a map legend for better clarity of interpretation.

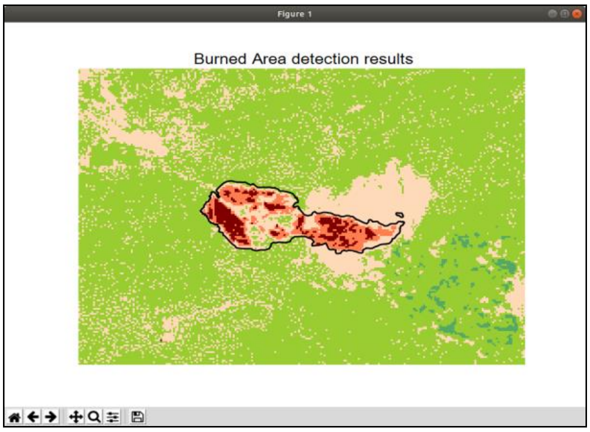

Fig. 8. Results of data analysis by ecomonitoring system

An analysis of the detection accuracy as a result of 50 epochs of learning was performed. A graph of the dependence of the detection accuracy (vertical axis) on the number of epochs of learning (horizontal axis) is shown in Fig. 9.

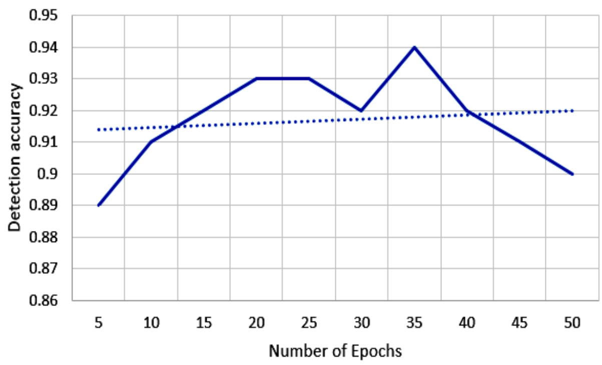

Fig. 9. Dependence graph of the detection accuracy of the test sample on the number of learning epochs

The spatial performance (detection accuracy) of the model is measured using Dice coefficient which is as a statistic used to gauge the similarity of two samples (also known as F_1 score) [15]:

$$Dice = \frac{2TP}{2TP + FP + FN}, \quad (3)$$

where TP, FP and FN are the number of true positives, the number of false positives and the number of false negatives, respectively.

The verification was carried out according to the following strategy: after every 5 epochs of training, 100 tiles with a known presence or absence of burned territory were randomly selected from the multispectral data set. Next, the tiles were presented as input data for the ML model, and the result of its analysis was compared with the predefined data. The overall detection accuracy was 0.917.

As a result of testing the developed system, it was determined that the accuracy of burned areas detection is sufficient enough to consider the proposed intelligent ecomonitoring system for practical use to solve the problem of automated Burned areas detection and improve the results of multispectral image analysis compared to analogue systems.

Conclusions

The article investigates and substantiates the application of intellectual methodologies for multispectral images processing.

The theoretical bases of construction of models of artificial intelligence in the field of analysis of multispectral data are considered.

The applied field of application in the field of ecological monitoring is chosen.

The architectural model of the software product is analyzed and offered taking into account its scalability, the software implementation is developed and the results of its work are shown.

The obtained results show the efficiency and prospects of the proposed algorithms, which is the reason for further research and improvement of the applied algorithms, with their possible implementation in industrial and enterprise eco-monitoring systems.

REFERENCES

1. Kvochka M. and Podorozhniak A. (2020), “Intelligent ecomonitoring solutions” [Vykorystannia zasobiv hlybynnoho navchannia u haluzi ekomonitorynhu], *Informatization problems, 7th International Conference on*: November 13-15, 2020, Cherkasy-Kharkiv-Baku-Balsko-Biala: Vol. 2., p. 51, available at: http://repository.kpi.kharkov.ua/bitstream/KhPI-Press/42754/1/Conference_NTU_KhPI_2019_Problemy_informatyzatsii_Ch_2.pdf.
2. Kvochka M. and Podorozhniak A. (2020), “Intelligent ecomonitoring solutions” [Intelektualni rishennia u haluzi ekomonitorynhu], *Modern development directions of information and communication technologies and controls, 10th International Conference on*: April 9-10, 2020, Baku-Kharkiv-Žilina: Vol. 1., p. 97, available at: http://repository.kpi.kharkov.ua/bitstream/KhPI-Press/53485/1/Podorozhniak_Intelektualni_2020.pdf.
3. Ramachandran B., Justice C.O. and Abrams M.J. (2011), *Land Remote Sensing and Global Environmental Change*, Springer, 873 p. DOI: https://doi.org/10.1007/978-1-4419-6749-7.
4. Chang-I C. (2013), *Hyperspectral Data Processing: Algorithm Design and Analysis*, John Wiley&Sons, 1st edition, 1164 p. DOI: https://doi.org/10.1002/9781118269787
5. Nahar, K. (2012), "Artificial neural network", *COMPUSOFT, An international journal of advanced computer technology*, Vol. 1, No. 2, pp. 25-27, available at: https://ijact.in/index.php/ijact/article/view/421/.
6. Dong H., Li T., Leng J., Kong L. and Bai G. (2017), “GCN: GPU-based Cube CNN Framework for Hyperspectral Image Classification”, *IEEE 46th International Conference on Parallel Processing* (ICPP), DOI: https://doi.org/10.1109/ICPP.2017.13
7. Podorozhniak A., Kvochka M. (2021), “Multispectral images processing using systems on chips”, *Modern development directions of information and communication technologies and controls, 11th International Conference on*: April 8-9, 2021, Baku-Kharkiv-Kyiv-Žilina: Vol. 2., p. 31, available at: http://repository.kpi.kharkov.ua/bitstream/KhPI-Press/52974/1/Podorozhniak_Multispectral_images_2021.pdf.
8. Vargas R., Mosavi A. and Ruiz R. (2018), "Deep learning: a review", *Advances in Intelligent Systems and Computing*, DOI: https://doi.org/10.20944/preprints201810.0218.v1.
9. Liubchenko N., Podorozhniak A. and Bondarchuk V. (2017), "Neural network method of intellectual processing of multispectral images", *Advanced information System*, Vol. 1, No. 2, pp. 39-44, DOI: https://doi.org/10.20998/2522-9052.2017.2.07.
10. Podorozhniak A., Lubchenko N., Balenko O. and Zhuikov D. (2018), "Neural network approach for multispectral image processing". *Advanced Trends in Radioelecrtronics, Telecommunications and Computer Engineering (TCSET-2018), 14th International Conference on*: IEEE, pp. 978-981, available at: http://dx.doi.org/10.1109/TCSET.2018.8336357.
11. Pinto M.M. (2021), “*Mapping burned areas from space with Artificial Intelligence*”, available at: https://medium.com/@mnpinto/mapping-burned-areas-from-space-with-artificial-intelligence-3657bdb97a9d.
12. Patterson J. and Gibson A. (2017), *Deep Learning: A Practitioner's Approach*, *O'Reilly Media*, 538 p. ISBN: 9781491914250.
13. Hui J. (2017), "Understanding Matrix capsules with EM Routing (Based on Hinton's Capsule Networks)", available at: https://jhui.github.io/2017/11/14/Matrix-Capsules-with-EM-routing-Capsule-Network/.
14. Hlavcheva D. and Yaloveha V. (2018), "Capsule neural networks", *Control, Navigation and Communication Systems*, Vol. 5, No. 51, pp. 132-135, DOI: https://doi.org/10.26906/SUNZ.2018.5.132.
15. Pinto M. M., Libonati R., Trigo R. M., Trigo I. F. & DaCamara C. C. (2020), "A deep learning approach for mapping and dating burned areas using temporal sequences of satellite images", *ISPRS Journal of Photogrammetry and Remote Sensing*, 160, 260–274, DOI: https://doi.org/10.1016/j.isprsjprs.2019.12.014.
16. Bengio, Y. (2009), "Learning deep architectures for AI", *Foundations and trends in Machine Learning*, Vol. 2, No. 1, pp. 1-127, DOI: https://doi.org/10.1561/2200000006.
17. Johnston B. and Mathur I. (2019), *Applied Supervised Learning with Python*, *Packt Publishing*, 2019, 404 p. ISBN: 9781789954920.
18. Pinto M. M. (2020), *BA-Net: A deep learning approach for mapping and dating burned areas using temporal sequences of satellite images*, available at: https://github.com/mnpinto/banet#train-the-model-from-scratch.
19. Mosavi A. and Varkonyi-Koczy A. R. (2017), "Integration of machine learning and optimization for robot learning", *Recent Global Research and Education: Technological Challenges*: Springer, pp. 349-355, DOI: https://doi.org/10.1007/978-3-319-46490-9_47.
20. McKinney W. (2017), *Python for Data Analysis*, 2nd Edition, O'Reilly Media, 544 p. ISBN: 9781491957660.

Надійшла (received) 15.07.2021
Прийнята до друку (accepted for publication) 08.09.2021

Подорожняк Андрій Олексійович – кандидат технічних наук, доцент, доцент кафедри обчислювальної техніки та програмування, Національний технічний університет “Харківський політехнічний інститут”, Харків, Україна;
Andrii Podorozhniak – Candidate of Technical Sciences, Associate Professor, Associate Professor of Computer Science and Programming Department, National Technical University "Kharkiv Polytechnic Institute", Kharkiv, Ukraine;
e-mail: andriipodorozhniak@gmail.com; ORCID ID: http://orcid.org/0000-0002-6688-8407.

Любченко Наталія Юріївна – кандидат технічних наук, доцент, доцент кафедри інформатики та інтелектуальної власності, Національний технічний університет “Харківський політехнічний інститут”, Харків, Україна;
Nataliia Liubchenko – Candidate of Technical Sciences, Associate Professor, Associate Professor of Computer science and intellectual property Department, National Technical University "Kharkiv Polytechnic Institute", Kharkiv, Ukraine;
e-mail: n_lubchenko@ukr.net; ORCID ID: http://orcid.org/0000-0002-4575-4741.

Квочка Микита Миколайович – студент-магістрант кафедри обчислювальної техніки та програмування, Національний технічний університет “Харківський політехнічний інститут”, Харків, Україна;
Mykyta Kvochka – student of Computer Science and Programming Department, National Technical University "Kharkiv Polytechnic Institute", Kharkiv, Ukraine;
e-mail: Mykyta.Kvochka@gmail.com; ORCID ID: http://orcid.org/0000-0003-0274-4065.

Суарес Іван – магістрант кафедри Систем, Автономний Столичний Університет (Аскапоцалько), Мехіко, Мексика;
Ivan Suarez – masters in computer science, Coordination of graduate studies, Department of Systems, Universidad Autonoma Metropolitana (Azcapotzalco), Mexico City, Mexico;
e-mail: al2181800100@azc.uam.mx; ORCID ID: http://orcid.org/0000-0002-4204-2183.

Застосування інтелектуальних методів мультиспектральної обробки даних у галузі екомоніторингу

А. О. Подорожняк, Н. Ю. Любченко, М. М. Квочка, І. Суарес

Анотація. Предметом вивчення в статті є методи штучного інтелекту, що можуть бути застосовані для розпізнавання конкретних ділянок земної поверхні на мультиспектральних зображеннях, наданих системами дистанційного зондування Землі. **Мета** – автоматизація аналізу даних для розпізнавання територій, уражених вогнем на мультиспектральних зображеннях ДЗЗ. **Задача** – дослідження і формулювання способу обробки мультиспектральних даних, що дозволяє автоматизувати процес оперативного розпізнавання на зображеннях ділянок вигорілих територій задля розробки програмної системи екомоніторингу із використанням таких засобів штучного інтелекту, як глибинне навчання та нейронні мережі. У результаті аналізу сучасних методів обробки мультиспектральних даних було обрано для дослідження застосування нейронних мереж зі стратегією навчання з учителем. Вибір описаних методів для вирішення прикладної задачі базується на високій гнучкості даних методів, а також, за умови достатнього обсягу використаних навчальних вхідних даних та коректних стратегій навчання, можливості аналізу різнорідних мульспектральних даних із забезпеченням високої точності результатів для кожної окремої вибірки. **Висновки:** досліджено та обґрунтовано застосування методологій інтелектуальної обробки мультиспектральних зображень. Розглянуто теоретичні основи побудови нейронних мереж, обрано прикладну галузь застосування. Проаналізовано та запропоновано архітектурну модель програмного продукту із урахуванням його масштабованості, проведено розробку програмної реалізації та показано результати її роботи. Отримані результати показують працездатність та перспективність запропонованих алгоритмів, що є приводом для подальшого дослідження і вдосконалення застосованих алгоритмів, із їх можливим впровадженням до промислових та корпоративних систем екомоніторингу.

Ключові слова: система екомоніторингу; дистанційне зондування Землі; мультиспектральне зображення; обробка зображень; нейромережа.

Применение интеллектуальных методов мультиспектральной обработки данных в сфере экомониторинга

А. А. Подорожняк, Н. Ю. Любченко, Н. Н. Квочка, И. Суарес

Аннотация. Предметом изучения в статье являются методы искусственного интеллекта, которые могут быть применены для распознавания конкретных участков земной поверхности на мультиспектральных изображениях, предоставленных системами дистанционного зондирования Земли. **Цель** - автоматизация анализа данных для распознавания территорий, пораженных огнем на мультиспектральных изображений ДЗЗ. **Задача** - исследование и формулирование способа обработки мультиспектральных данных, позволяющего автоматизировать процесс оперативного распознавания участков выгоревших территорий на изображениях, для разработки программной системы экомониторинга с использованием таких средств искусственного интеллекта, как глубокое обучение и нейронные сети. В результате анализа современных методов обработки мультиспектральных данных было выбрано исследование применения нейронных сетей со стратегией обучения с учителем. Выбор описанных методов для решения прикладной задачи базируется на высокой гибкости данных методов, а также, при условии достаточного объема использованных учебных входных данных и корректных стратегий обучения, возможности анализа разнородных мульспектральних данных с обеспечением высокой точности результатов для каждой отдельной выборки. **Выводы**: исследовано и обосновано применение методологий интеллектуальной обработки мультиспектральных изображений. Рассмотрены теоретические основы построения нейронных сетей, выбрана прикладная область применения. Проанализирована и предложена архитектурная модель программного продукта с учетом его масштабируемости, проведена разработка программной реализации и показаны результаты ее работы. Полученные результаты показывают работоспособность и перспективность предложенных алгоритмов, что является поводом для дальнейшего исследования и совершенствования применяемых алгоритмов, с их возможным использованием в промышленных и корпоративных системах экомониторинга.

Ключевые слова: система экомониторинга; дистанционное зондирование Земли; мультиспектральное изображение; обработка изображений; нейросеть.