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V. Yu. Kashtan,
orcid.org/0000-0002-0395-5895,
V. V. Hnatushenko*,
orcid.org/0000-0003-3140-3788,
I. S. Laktionov,
orcid.org/0000-0001-7857-6382,
H. H. Diachenko,
orcid.org/0000-0001-9105-1951

Dnipro University of Technology, Dnipro, Ukraine
* Corresponding author e-mail: vvgnat@ukr.net

INTELLIGENT SENTINEL SATELLITE IMAGE PROCESSING TECHNOLOGY FOR LAND COVER MAPPING

Purpose. This article proposes to develop an intelligent Sentinel satellite image processing technology for land cover mapping using convolutional neural networks. The result will be an image with improved spatial resolution.

Methodology. The paper presents a technology using a combination of biquadratic interpolation, histogram alignment, PCA transform, as well as a parallel residual architecture of convolutional neural networks. The technology increases the information content of Sentinel-2 optical images by combining 10 and 20-meter resolution data, resulting in primary 20-meter images with improved spatial resolution.

Findings. The root mean square error (RMSE = 3.64) indicates a high accuracy in reproducing the spectral properties of the images. The correlation coefficient (CC = 0.997) confirms a high linear relationship between the estimated and observed images. The low value of Spectral Angle Mapper (SAM = 0.52) with the high Universal Image Quality Index (UIQI = 0.999) indicates high quality and structural similarity between the synthesized and reference images. These results confirm the proposed technology's effectiveness in enhancing the spatial resolution of Sentinel satellite images.

Originality. Traditional pansharpening methods of multispectral images developed for satellite images with panchromatic channels cannot be directly applied to Sentinel multispectral data, because these images do not contain a panchromatic channel. In addition, atmospheric conditions and the presence of clouds affect the quality of optical images, complicating their further thematic processing. The proposed technology, using biquadratic interpolation, histogram alignment, convolutional neural networks, and PCA transformation, removes clouds and enhances the spatial resolution of the primary 20-meter optical satellite image channels of Sentinel-2. This technology reduces color distortion and increases the detail of digital optical images, which allows for more accurate analysis of the state of the earth's surface.

Practical value. The results obtained can be used to improve the methods for processing Sentinel satellite images, which provide high spatial resolution and accurate preservation of spectral characteristics. It provides the foundation for the development of new geographic information systems for land cover monitoring.

Keywords: *convolutional neural network, image, remote sensing, spatial resolution*

Introduction. Today, many of the world's most pressing problems are directly or indirectly related to agricultural production [1] and smallholder farming. Ukraine's agricultural sector is a source of exports to the Americas, the European Union, and Asia. Intensive development of this sector contributes to economic growth and strengthening of international economic relations. Studies show that Ukraine is significantly ahead of countries with similar climatic conditions regarding exports and profitability. For example, in 2023, Ukraine exported 16.1 million tons of wheat to 65 countries, 26.2 million tons of corn to 80 countries, and 5.7 million tons of sunflower oil to 130 countries. As the population grows and diets change, enhancing agricultural production is crucial to ensuring global food security [2, 3]. Thus, political instability affects the stability of the farm sector, calling into question traditional monitoring methods due to high financial costs and risks to workers. Therefore, it is necessary to conduct reliable and accurate agricultural monitoring to maintain the balance of all services provided by the ecosystem [4, 5].

Due to modern technologies such as satellite Earth observation and cloud technologies, new opportunities for agricultural monitoring are opening up. These tools make it possible to provide detailed information about crops at the national level in farming systems. For example, the European Space Agency (ESA), as part of the Copernicus program, provides free and open data from Sentinel-1 and Sentinel-2 satellites and allows for detailed information on the condition of agricultural land. The radiometric resolution of these satellites will enable one to recognize different types of agricultural crops by measuring reflectivity at other wavelengths, including visible, near-infrared, and mid-infrared. The temporal resolution is necessary for monitoring dynamic processes, such as changes in the growing season of agricultural crops, which allows us to assess the phases of plant growth and development.

Optical images from Sentinel-2 consist of 13 spectral channels in the visible, near-infrared (NIR), and short-wave infrared (SWIR) bands. The spatial resolution of these images includes 10, 20 and 60 m bands. The 10 m resolution bands (Band 2, Band 3, Band 4 and Band 8) are optimal for detailed analysis and mapping. In comparison, the 20 m (Band 5, Band 6, Band 7, Band 8a, Band 11 and Band 12) and 60 m (Band 1, Band 9 and Band 10) contain important spectral information needed to assess the state of agricultural land vegetation, determine chlorophyll content, water stress, and atmospheric correction. Agriculture requires accurate spatial data for effective management. The satellite images from Sentinel-2 spacecraft usually do not meet these requirements due to low pixel resolution. The 20 and 60 m bands do not provide sufficient detail to identify fields, crop boundaries, and other agronomic objects. It creates difficulties in mapping, monitoring, and managing agricultural land.

A significant portion of remote sensing data is in a digital form. The industry is shifting to digital methods for processing remote information. It raises the issue of choosing the best techniques and algorithms for processing satellite data. Significant difficulties can arise at the pre-processing stage, as there are often no universal approaches to enhance the primary image. In addition, the same land area can be acquired from space in different periods using different sensors, spectral bands, and resolutions. For successful data analysis, it is necessary to combine and process it, which requires accurate coordinate alignment of images at the sub-pixel level. Most traditional algorithms for pre-processing and thematic processing of satellite images, such as iterative register correction methods or complex filtering algorithms, involve numerous mathematical operations, including multi-stage transformations and conversions. These algorithms are resource-intensive for rapid processing of large amounts of data and also do not always provide the required accuracy due to errors in real-world variable image characteristics, such as different lighting conditions or atmospheric interference. One of the widely used pre-processing methods is pan-sharpening. This method combines images with different spatial resolutions to create a new image with increased detail. Pansharpening uses satellite imagery (e.g., Worldview and Landsat), which contains a high-resolution panchromatic channel and lower spatial resolution multispectral channels. However, in the case of Sentinel-2 satellites, the lack of a panchromatic channel makes it difficult to apply traditional pansharpening methods directly. Therefore, to achieve high accuracy in the allocation and analysis of agricultural land based on Sentinel-2 data, there is a need to develop alternative approaches to increase the spatial resolution of the channels from 20 and 60 to10 meters [6].

Literature review. Satellite image processing methods are divided into two main categories: pre-processing and thematic processing. Pre-processing covers image enhancement, correction, and restoration. Thematic processing focuses on extracting information from the images. Pre-processing methods aim to transform images to facilitate visual analysis, enhance the informativeness and accuracy of the data, and prepare the samples for further automated analysis and map creation. Thematic processing methods use automated image analysis to classify objects on the images, either with or without a priori information about the characteristics of the classes to be identified.

Increasing image information content is the main stage of pre-processing. The main approaches to image fusion are component substitution (CS), multiple resolution analysis (MRA) [7], and pan-sharpening. In the CS approach, the original multispectral image transforms into a new domain by replacing one of the components with a band of thin spatial resolution, such as a panchromatic (PAN) band. Common examples of CS include principal component analysis [8], intensity-hue-saturation (IHS) [9], Brovey transform (BT), Gram-Schmidt transform (GS) [10], adaptive GS (GSA), and partial replacement adaptive component substitution (PRACS).

A spatial detail is introduced in the MRA approach by repeatedly decomposing a thin band. It includes high-pass filtering (HPF), smoothing filtering based on intensity modulation (SFIM), wavelet transform [11], additive wavelet transform (ATWT) [12], ATWT using model 2 (ATWTM2) and model 3 (ATWT-M3), and generalized Laplace pyramid with modulation transfer function matched filter (MTF-GLP).

The information content of Sentinel-2 images is enhanced by synthesizing 10-meter bands as a panchromatic channel to enhance the spatial resolution of 20-meter bands [13]. The obtained results are used for land cover classification [14]. However, to take into account the peculiarities of Sentinel-2 images, four high-resolution bands used to enhance the resolution of 20 and 60 m bands do not contain spatial information that is characteristic of the panchromatic channel; the spectral range of high-resolution bands should not overlap with the ranges of low-resolution bands. Therefore, using pansharpening methods is restricted to enhancing the informativeness of Sentinel-2 images.

Geostatistical approaches, such as kriging interpolation, increase the information content through image fusion. For example, the kernelized external drift (KED), downscaling kernelization (DSCK), and area-total regression kernelization (ATPRK) methods have a significant advantage in that they preserve the spectral properties of the observed raw images, i.e., they are coherent. However, ATPRK is computationally more efficient and user-friendly than KED and DSCK.

Traditional methods for preliminary and thematic processing of satellite images analyze spatial, spectral, textural, morphological, and other characteristics. However, shallow learning analytical approaches, which use images with high spatial resolution but low spectral and temporal resolution, often fail to effectively distinguish land use classes due to similarity in spectral signatures. Instead, deep learning, which is multi-level and uses the data for training, performs significantly better than shallow methods and has already been proven to outperform manual results. In a study [15], the authors trained a high-resolution deep residual neural network on Sentinel-2 images using a large training data set. Convolutional Neural Networks (CNNs), as a form of deep learning, can use contextual and spectral information to analyze images [16]. The study [17] developed an extended convolutional neural network structure for fusing Sentinel-2 and Landsat 8 images. Although deep learning methods effectively increase the information content of satellite images, their use has certain limitations. For example, publicly available satellite images often have a large coverage area and low spatial resolution, which does not meet the requirements of convolutional neural networks. Article [18] notes that improving land cover mapping requires integrating computer vision technologies with traditional methods of Earth image analysis.

Purpose. This study aims to develop an intelligent Sentinel satellite image processing technology for agricultural land mapping using convolutional neural networks. The result will be an image of the primary 20-meter channels with improved spatial resolution to using 10-meter Sentinel-2 channels. This approach is expected to improve the accuracy and detail of the obtained images, which is crucial for the successful use of Sentinel data in agricultural monitoring.

In this paper, to achieve the set aim, the following tasks were formed and solved:

- to develop a methodology using convolutional neural networks for cloud masking and removal based on the integrated use of Sentinel-1 and Sentinel-2 images, and a parallel residual architecture for combining and enhancing image information;
- to optimize the image processing algorithms within this methodology to ensure accurate detection and increase the information content of Sentinel images;
- to conduct a comprehensive evaluation and comparison of the proposed methodology with traditional methods, evaluating factors such as accuracy, efficiency, and computational performance;
- to test the effectiveness and applicability of the developed methodology by applying it to real datasets, with an emphasis on increasing the information content of Sentinel images for agricultural monitoring.

Methods. The paper proposes to use a parallel residual architecture based on convolutional neural networks to combine and increase the information content of Sentinel-2 images. Fig. 1 shows the block diagram of the information technology.

The first step is to load Sentinel-1 and Sentinel-2 spacecraft images from the ESA website.

The second step is the pre-processing of satellite images. The Sentinel-1 geospatial data are corrected according to the algorithm presented in [19]. For optical images from the Sentinel-2 satellite, the following steps are included: geometric correction, radiometric calibration, and brightness conversion. Geometric correction improves the quality of the primary image by eliminating various artifacts that arise from camera angles, positional inaccuracies, and the influence of terrain and atmospheric conditions. It is proposed to use the bi-quadratic interpolation method for geometric image correction (resampling). This method considers the number of pixels included in the updated values. This method uses the OpenCV image processing library of the Python programming language. After processing the image using the bi-quadratic interpolation method, a new value is calculated around each pixel based on the values of the neighboring pixels. It helps to correct geometric distortions and convert data into geographic coordinates.

Radiometric calibration is the process of minimizing the difference in brightness values between images that can occur due to sensor defects or atmospheric noise. The histogram equalization method is used for the radiometric correction of satellite images [20]

$$G(z) = \frac{L-1}{MN}\sum_{j=0}^{z} n_j,$$

where $G(z)$ is the new intensity value for pixels from the source image; z is the pixel intensity value; L is the maximum intensity value (usually 256 for an 8-bit image); M and N are the image sizes; n_j is the number of pixels from the source image with intensity j.

At the third step of the correction procedure, we obtain radiometrically and geometrically corrected satellite images in a cartographic coordinate system.

The fourth step is to perform the masking procedure and remove clouds and artifacts that may affect the accuracy of the analysis [21]. The cloud masking procedure uses the convolutional neural network (CNN) architecture consisting of layers with three-dimensional organization: width, height, and depth. It allows for efficient processing of multi-channel data. In the layers, limited regions of the input image connect to the neurons before proceeding through the convolution process. It significantly reduces the number of parameters and weights the model needs to train. One of the unique features of ANNs is their capacity to identify the optimal filters during training. It makes it possible to extract features at different levels of image complexity. Each convolutional layer extracts progressively complex features, functioning as filters to separate clouds and shadows. The convolutional architecture performs operations in both spectral and spatial aspects. Convolutional layers preserve the spatial relationship between pixels, enabling the analysis of image features. Pooling layers (sub-sampling) then reduce the dimensionality of each feature map while retaining the most relevant information about the image. The convolution process is mathematically defined as follows [22]

$$G_i = f(G_{i-1} \otimes W_i + b_i),$$

where W_i is the vector of weighting coefficients of the i^{th} convolution filter; symbol $\otimes$ represents the convolution operation between the i^{th} image layer and the i-1^{th} layer; b_i is the shift vector; the feature map G_i of the i^{th} layer is obtained using a linear activation function $f(\bullet)$.

The pooling operations apply various data aggregation methods, such as maximum, average, or sum. The quantity of convolution and merge operations, as illustrated in Fig. 1, is dictated by the number of filters utilized in each layer. At this step, the multi-channel images (in RGB format) of the patches, transformed from the Sentinel-2 dataset using PCA, are used in the data. The architecture has four hidden layers (with kernel sizes of 3×3, 3×3, 5×5 and 5×5) and a final layer with two outputs corresponding to the "cloudless" and "cloudy" classes.

The proposed technology leverages content, texture, and spectral information across each dimension. It constructs a low-rank adaptive weighted tensor regularization model for restoring cloudy areas. This model includes an object recovery network that recovers missing objects in the image, a spectral feature recovery network that recovers spectral information about these objects, and a texture recovery network that helps improve the quality of the recovery. Each layer of the convolutional network is activated using corrected linear units (ReLUs) [22]

$$\mathrm{ReLU}(x) = \max(0, x)$$

A loss function recovers cloudy areas by comparing images containing clouds (Sentinel-2) with cloud-free images (Senti-

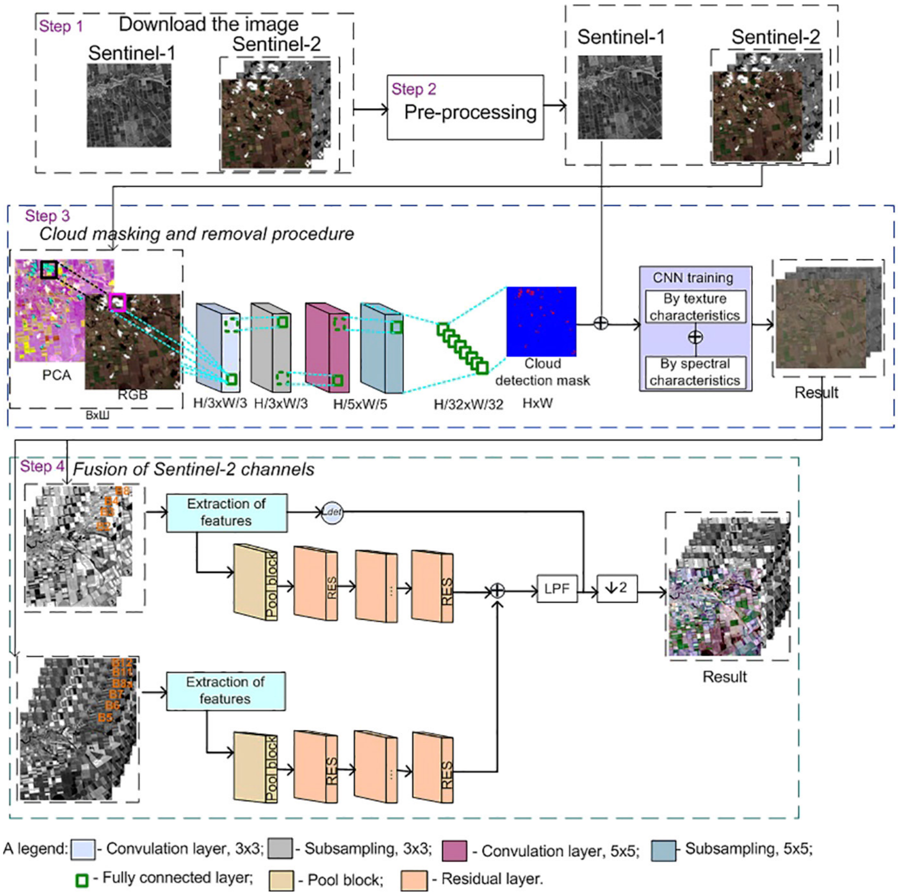

Fig. 1. Proposed information technology framework

nel-1). The root mean square error serves as the loss function and is calculated by comparing the original and predicted pixel intensity values of images. Specifically, the root mean square error is defined as the average of the squared differences between the pixel intensities at corresponding positions in the two images [23]

$$L(X_1, Y_i) = \frac{1}{2N} \sum_{i=1}^{N} \| X_1 - Y \|_2^2,$$

where N denotes the amount of additional data; X_l is a time snapshot with areas covered by the cloud; Y_i is additional data, such as spectral or temporal data.

The output feature map *GNN_output* was calculated based on the input feature maps G_{CNN_1} and G_{CNN_2}, which were obtained from CNN. The V function applies to the output obtained from the previous convolutional operation

$$GNN\_output = G_{CNN\_1} + V(C(G_{CNN\_1}, G_{CNN\_2})),$$

where *GNN_output* is the result of a CNN containing content-texture-spectral characteristic data; G_{CNN_1} is a feature map created by a texture CNN; G_{CNN_2} is a feature map created by a spectral CNN; $C(G_{CNN\_1}, G_{CNN\_2})$ is all input feature maps obtained by concatenating G_{CNN_1} and G_{CNN_2}; $V(G_{CNN\_1}, G_{CNN\_2})$ is a feature map obtained by convolutional operation with a kernel that uses $C(G_{CNN\_1}, G_{CNN\_2})$ as input.

A parallel residual architecture utilizing convolutional neural networks is proposed to combine and enhance the information content of Sentinel-2 images. The Sentinel-2 image data is divided into two sets with 10-meter and 20-meter resolution. Band 10 is excluded from the spatial enhancement due to its low radiometric quality and cross-band artifacts [22]. Given these sets, the proposed spatial enhancement of the data is to use the 10-meter resolution version of the VHRP in the 20-meter bands. It is important to note that channels B5, B6 and B7 contain important information for estimating soil moisture and forecasting weather conditions to optimize agricultural processes. Band B8a measures the photosynthetic activity of plants, which is a critical indicator for evaluating plant health and growth. Bands B11 and B12 are used to measure temperature changes on the land surface. It allows the detection of thermal anomalies and develops strategies for managing thermal resources. Thus, the information contained in the 20-meter channels is necessary for the land-based agricultural sector, as it allows for accurate monitoring and evaluation of various aspects of crop production and land management.

The next step is to apply the feature extraction block, which has two branches: the first branch contains the pooling (subsampling) and residual layer blocks, and the second branch contains the detailed loss components. Additional 20-meter Sentinel-2 image channels load through the feature extraction block in parallel. The data from both branches are combined, and the result is subjected to low-pass filtering to reduce noise and remove high-frequency components. Next, add the detailed loss components, previously calculated, to the resulting data. Subsequently discretize the result to achieve the final enhancement of image information. A spatial feature fusion component combines information from various resolution ranges. After the parallel residual learning component, the obtained feature maps combine and transfer to the next level. Utilize two fully connected layers, each followed by ReLU activation. Next, the convolution layer transforms the feature maps into a spatial residual image, matching the channel count of the high-resolution images [24]

$$\begin{cases} z_{f1} = \mathrm{Re}\,LU(w_{f1} \cdot z + b_{f1}) \\ z_{f2} = \mathrm{Re}\,LU(w_{f2} \cdot z_{f1} + b_{f2}), \\ z_2 = w_{f3} \cdot z_{f2} + b_{f3} \end{cases} \quad (1)$$

where z is the output data obtained after the previous convolution operation; z_{f1} is the output data of the first fully connected layer (FC); z_{f2} is the output data of the second layer; z_2 is the final output; w_{f1}, w_{f2}, w_{f3} is FC layer weights; b_f, b_{f2}, b_{f3} is FC layer displacements.

Thus, in formula (1), the variable z denotes the output after the preliminary convolution operation applied to the input image. After this operation, the resulting feature maps are sent to the first fully connected layer, denoted as z_{f1}. Then, using the weights w_{f1} and bias b_{f1}, this data is processed by applying the activation function ReLU.

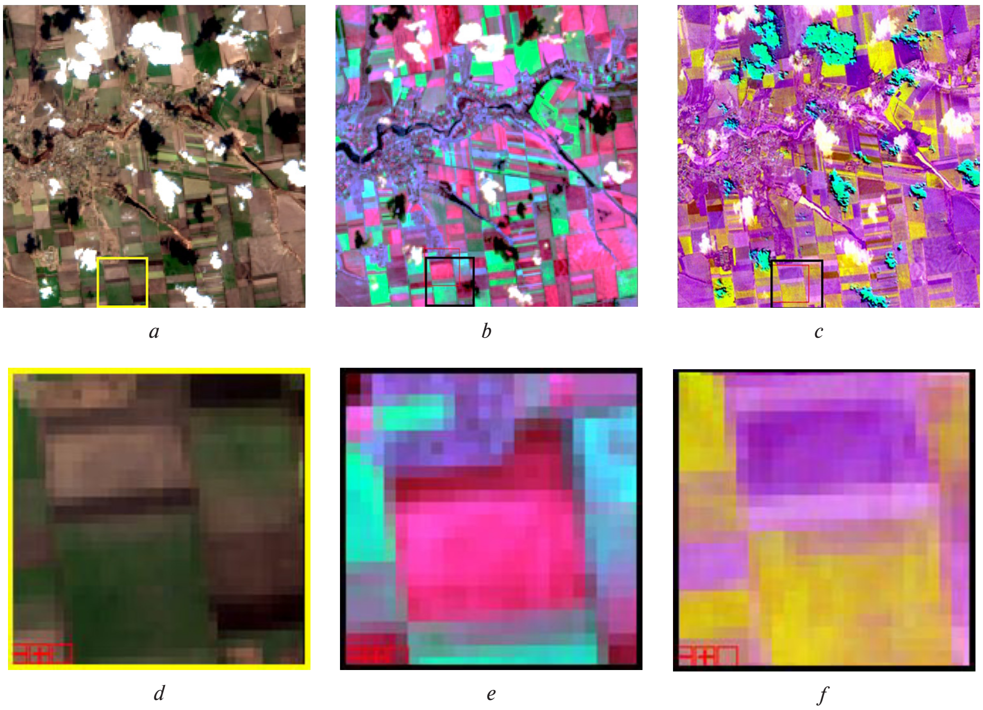

Fig. 2. The Sentinel-2 data set used in the experiments:

a – 10-meter data (channels 4-3-2 in RGB); b – 20-meter data (channels 12-8A-5 in RGB); c – result after PCA transformation; d – under the 10-meter data area; e – under the 20-meter data area; f – under the PCA transformation area

Results. This work proposes to use experimental data from the Sentinel-2 Level-1C spacecraft. The training data covers the scene of the village of Velyka Bilozerka in Zaporizhzhia region of Ukraine in the spring of 2023.

During this period, farmers are preparing fields for the sowing campaign. The study showed that in the period from spring to summer, cloud cover in Velyka Bilozerka village increases compared to other seasons. It is due to the characteristic meteorological conditions during this period, such as more intense cyclones and the spread of moisture from the Atlantic Ocean due to the influence of spring irrigation. Such increased cloud cover can affect the efficiency of data collection from artificial satellites, in particular, reduce image quality and complicate the process of analyzing land data. Fig. 2 shows 10-meter and 20-meter data channels.

During the experiments, the parameters of the proposed technology in this paper were as follows: first, train the parallel residual architecture of convolutional neural networks (ResNet)3x on 60×60 pixel patches of data reduced by a factor of 2. Similarly, to train a parallel residual network based on ResNet5x, the data was reduced by a factor of 5 and combined into 20×20 pixel patches. Train each network with 3,600 pairs of samples and allocate 10 % of these samples for data validation. Each branch contains 5 ResBlocks, and the 3×3 convolutional layers use 128 filters, except for the final convolutional layer. The Keras framework implemented the networks used. Fig. 3 presents the results from both the experimental settings

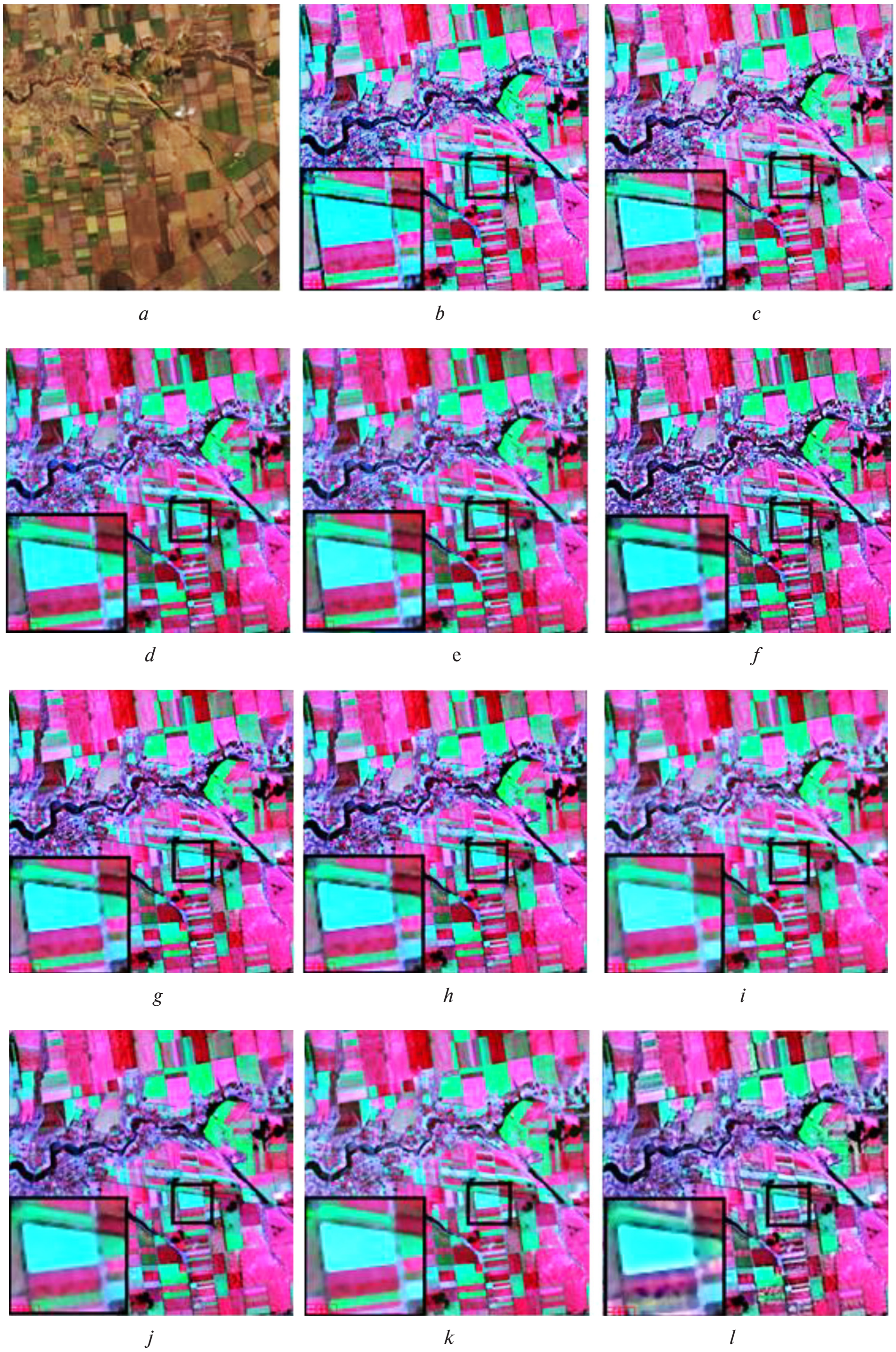

Fig. 3. Results of Sentinel-2 image information enhancement:

a – original image; b – proposed technology; c – ATWT; d – AWLP; e – Brovey; f – GS; g – HCS; h – HPF; i – HPFC; j – LMM; k – LMVM; l – HIS and traditional processing methods, enabling a comparison of their impact on the information content of the images.

To compare the effectiveness of the proposed method with existing methods (ATWT, AWLP, HPF, GS, HCS, LMM, Brovey, IHS, HPFC, and LMVM), evaluators used quality metrics for each method based on Sentinel-2 images. They assessed the methods using RMSE (Root Mean Square Error), CC (Correlation Coefficient), ERGAS (Relative Global Error), SAM (Spectral Angle Mapper), UIQI (Universal Image Quality Index), and SRE (Spectral Reconstruction Error). Table presents the results. To analyze the quantitative performance of traditional image processing methods from Table, we can conclude that the proposed technology demonstrates better results: the low RMSE value (3.64) indicates high accuracy of spectral properties reproduction, and the high CC correlation coefficient (0.997) confirms a solid linear relationship between the estimated and observed images. In addition, the low SAM value (0.52) and high UIQI (0.999) indicate high quality and structural similarity between the calculated and observed images. These results demonstrate the effectiveness of the proposed method in reproducing the spectral properties of Sentinel-2 images.

The HPFC method is not effective among the investigated methods. This method has the highest values of each metric compared to the other methods, indicating its low efficiency in reproducing the spectral characteristics of Sentinal-2 images.

To test the effectiveness of the technology on real Sentinel-2 data, we directly loaded the original low-resolution datasets and the high-resolution data into the trained networks. This means that the (20, 10 m) resolution datasets obtain the high-resolution 10 m images. Since there are no ground data available, spectral bands with higher resolution were considered as reference data to evaluate the effectiveness of the resolution enhancement method. As part of the experiments, four spectral bands with a resolution of 10 m were used as reference data for visual evaluation of the results. The results of the image processing methods shown in Fig. 3 confirm that the proposed technology significantly improves the sharpness of edges and the saturation of details of ground objects.

The image reconstructed using the ATWT method demonstrates the preservation of spectral and spatial characteristics, but some artifacts in the form of noise and blurring are observed. The result of applying the AWLP method is characterized by high-quality preservation of details and colors. The image has clear contours and low noise. The image obtained using the Brovey method reproduces the spectral characteristics with high accuracy, but there are artifacts in the form of blurring and color saturation. The GS method resulted in an image with a certain level of blurring and loss of detail, especially in areas with thin contours. The image produced by HCS reproduces details with the specified accuracy, but there are artifacts in the form of noise and low resolution. The image created by the HPF method is characterized by high resolution and sharp details, but noise is present. The HPFC method resulted in a significant loss of detail and a high level of blurring in the image. The image reconstructed using the IHS method has some artifacts in the form of color saturation and loss of detail in dark areas. The LMM method provides high-quality reproduction of image details and colors without noticeable noise. The image obtained by the LMVM method has clear details and colors without noticeable noise or artifacts. The image obtained using the proposed method reproduces spectral and spatial characteristics with high accuracy and minimal artifacts.

Fig. 4 shows a graph of the execution time of image processing methods. The fastest method is Brovey, which runs in just 0.016 seconds due to its simple computational procedure. On the other hand, the slowest method is LMVM, and the proposed technology is due to a more complex computational procedure and a large amount of data to be processed.

This study implemented the proposed technology on a personal computer with an Intel(R) Core(TM) i5-7400 CPU running at 3.00 GHz, an Nvidia GTX 950M graphics processor, and 16 GB of RAM. This configuration made it possible to train the convolutional neural network. After completing the training process of the artificial intelligence model, the team designed the general architecture of the developed software application. Fig. 5 displays the sequence and steps of applying the image processing technology.

Python programming language implements the software for the proposed information technology. The development involved libraries such as TensorFlow, NumPy, Matplotlib, Rasterio, GeoPandas, and Earthpy. These libraries facilitated data handling, result visualization, and the implementation of image processing techniques.

Conclusions. The paper proposes an intelligent technology for processing Sentinel satellite images for mapping agricultural lands using convolutional neural networks. The developed technology integrates Sentinel radar and optical images using biquadratic interpolation, histogram alignment, convolutional neural networks, and PCA transformations for cloud masking and removal. It is proposed to use the parallel residual CNN architecture, which allows combining data with different resolutions (10 and 20 meters) and increasing the information content of Sentinel-2 optical images. The proposed technology reduces color distortion and increases the detail of digital optical images, which makes it possible to more accurately identify

Table

Quantitative assessments

Method	Metrics					
	RMSE	CC	ERGAS	SAM	UIQI	SRE
ATWT	11.29	0.97	16.47	5.27	0.98	0.01
AWLP	10.25	0.97	16.01	4.81	0.98	0.01
HPF	13.94	0.95	19.46	6.48	0.99	0.02
GS	10.92	0.96	63.77	5.18	0.95	0.01
HCS	13.20	0.96	13.24	5.98	0.99	0.02
LMM	8.38	0.97	19.95	3.96	0.98	0.04
Brovey	10.34	0.96	69.33	4.89	0.95	0.01
IHS	12.29	0.95	71.30	5.82	0.99	0.01
HPFC	17.04	0.95	22.27	6.19	0.98	0.01
LMVM	13.59	0.95	20.62	6.37	0.99	0.01
Proposed technology	3.64	0.99	5.91	0.52	1	0

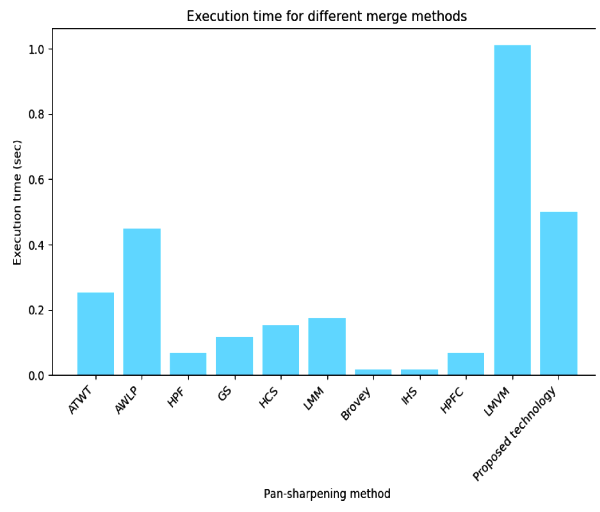

Fig. 4. Execution Time of Various Image Processing Methods

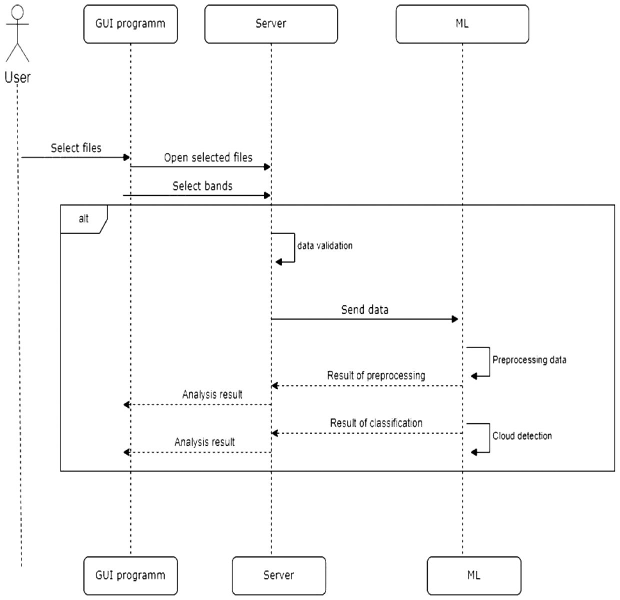

Fig. 5. The sequence diagram

the boundaries of agricultural fields and analyze the condition of the land in detail. Experimental results confirm the effectiveness of the proposed approach: Root mean square error (RMSE = 3.64), high correlation coefficient (CC = 0.997), lowest extended normalized difference vegetation index (ERGAS = 5.91), low spectral angle of reflection (SAM = 0.52), high universal image quality index (UIQI = 0.999) and minimum value of spectral residual error (SRE = 0) indicate the success of the developed methods. The results obtained can be used to improve the methods for processing Sentinel satellite images, which provide high spatial resolution and accurate preservation of spectral characteristics. This development provides a foundation for improved geographic information technologies, which can be applied to land cover monitoring.

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Інтелектуальна технологія обробки супутникових зображень Sentinel для картографування земного покриву

В. Ю. Каштан, *В. В. Гнатушенко**, *І. С. Лактіонов*, *Г. Г. Дяченко*

Національний технічний університет «Дніпровська політехніка», м. Дніпро, Україна

* Автор-кореспондент e-mail: vvgnat@ukr.net

Мета. Розробка інтелектуальної технології обробки супутникових зображень Sentinel за допомогою згорткових нейронних мереж. У результаті синтезується зображення із покращеною просторовою роздільною здатністю.

Методика. Представлена інтелектуальна технологія, що використовує комбінацію методів біквадратичної інтерполяції, гістограмного вирівнювання та PCA-перетворення, а також паралельну залишкову архітектуру згорткових нейронних мереж. Використання технології підвищує інформативність оптичних зображень Sentinel-2 завдяки об'єднанню даних із роздільними здатностями 10 і 20 метрів. У результаті отримаємо первинні 20-метрові зображення з покращеною просторовою роздільною здатністю.

Результати. Середньоквадратична похибка (RMSE = = 3,64) свідчить про високу точність відтворення спектральних властивостей зображень. Коефіцієнт кореляції (CC = 0,997) підтверджує дуже сильну лінійну залежність між оціненими та спостережуваними зображеннями. Низьке значення спектрального кута відображення (SAM = 0,52) разом із високим універсальним індексом якості зображення (UIQI = 0,999) свідчать про високу якість і структурну подібність між синтезованими та еталонними зображеннями. Результати тестування підтверджують ефективність запропонованої технології у покращенні просторової роздільної здатності супутникових зображень Sentinel.

Наукова новизна. Класичні методи підвищення інформативності багатоспектральних зображень розроблені для супутникових знімків із панхроматичними каналами, не можуть бути безпосередньо застосовані до знімків супутника Sentinel, оскільки ці зображення не містять панхроматичний канал. Крім того, атмосферні умови, зокрема наявність хмар, впливають на якість оптичних знімків, ускладнюючи їх подальшу тематичну обробку. Запропонована технологія на основі методів біквадратичної інтерполяції, гістограмного вирівнювання, згорткових нейронних мереж і PCA-перетворення дозволяє видаляти хмари на знімках і покращувати просторову здатність первинних 20-метрових каналів оптичних супутникових зображень Sentinel-2. Ця технологія дозволяє зменшити кольорові спотворення й підвищити деталізацію цифрових оптичних зображень, що дає змогу в подальшому більш точно аналізувати стан земного покриву.

Практична значимість. Отримані результати можуть бути використані для вдосконалення методів обробки супутникових зображень Sentinel, що забезпечують отримання геопросторових даних покращеної просторової здатності зі збереженням спектральних характеристик. Це створює основу для розробки нових геоінформаційних систем для моніторингу земної поверхні.

Ключові слова: *згорткова нейронна мережа, зображення, дистанційне зондування, просторова здатність*

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