*The information technology that implements evaluation of redundant information using the methods of preprocessing and segmentation of digital images has been devised. The metrics for estimating redundant information containing a photo image using the approach based on texture variability were proposed. Using the example of aerial photography data, practical testing and research into the proposed assessment were carried out.*

*Digital images, formed by various optoelectronic facilities, are distorted under the influence of obstacles of various nature. These obstacles complicate both the visual analysis of images by a human and their automatic processing. A solution to the problem can be obtained through preprocessing, which will lead to an increase in the informativeness of digital image data at a general decrease in content.*

*An experimental study of the dependence of image informativeness on the results of overlaying previous filters for processing digital images, depending on the values of parameters of methods, was carried out. It was established that the use of algorithms sliding window analysis can significantly increase the resolution of analysis in the time area while maintaining a fairly high ability in the frequency area. The introduced metrics can be used in problems of computer vision, machine and deep learning, in devising information technologies for image recognition. The prospect is the task of increasing the efficiency of processing the monitoring results by automating the processing of the received data in order to identify informative areas. This will reduce the time of visual data analysis. The introduced metrics can be used in the development of automated systems of air surveillance data recognition*

*Keywords: computer vision, image recognition, digital image informativeness, image preprocessing*

# DEVISING INFORMATION TECHNOLOGY FOR DETERMINING THE REDUNDANT INFORMATION CONTENT OF A DIGITAL IMAGE

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## 1. Introduction

Computer vision systems are designed to solve, and in many cases already solve, the problem of supplementing or even replacing a human in the areas of activities related to the collection and analysis of visual information. The level of their use in applied areas is one of the most vivid and clear integral indicators of the level of development of high technologies in a wide variety of fields of science and industry.

Despite the significant progress made in the field of computer vision, its effective use as a means of automation accounts primarily for the most developed production with general high culture and technology.

Computer vision tasks include analysis of scenes, processes, phenomena in order to select the objects with specified characteristics or properties, that is, extracting information about these objects. In general, informativeness implies the aggregate amount of information received by a consumer on spatial, spectral-energy, temporary, and other features during their perception and analysis. Digital images, formed by various optic and electronic facilities, are distorted under the influence of obstacles of various nature. All distortions added to a digital image are called noise or redundant informativeness of a digital image. Noise complicates both the visual analysis of human images and their automatic processing. Many methods for image enhancement reduce

the impact of noise added during the process of digital image formation. But it is interesting for developers to determine redundant informativeness after applying a certain image processing algorithm.

It is necessary to state the fact that there is no universal mathematical apparatus that would make it possible to form a general formalized approach to the construction of computer vision systems. There is no unified approach to determining the informativeness of a digital image. Such facts substantiate the relevance of research in this direction.

## 2. Literature review and problem statement

According to source [1], the researchers distinguish three main approaches to assessing the information amount:

1. Structural approach in the discrete generation of an information array, the amount of information is measured by calculating its information elements.

2. Statistical approach operates the concept of entropy as a degree of situation uncertainty. Entropy takes into consideration the possibility of the situation's appearance, and therefore the informativeness of a message.

3. Semantic approach takes into consideration the value, usefulness of the information. Currently, the application is limited because the theory was not sufficiently developed.

From the traditional approaches to the assessment of informativeness, one should note the classic method for calculating the entropy of messages [2]. The development of the theory of entropy of messages is reflected in work [3]. The entropy of an arbitrary message implies the average amount of information in a message that falls on a single character. Entropy characterizes the message in terms of its information saturation. The greater the entropy, the more information is perceived in a unit of time. Information entropy also characterizes a measure of uncertainty or unpredictability of information. In paper [4], it is noted that Shannon's approach allows fair objective assessment of the informativeness of an ideal communication channel (without interference and noise). But it can be senseless for actual images because it does not take into consideration spatial dependences of the brightness of the image elements and the peculiarities of their visual perception.

In [5], the image informativeness assessment is identified with the image quality assessment. A totality of local statistical indicators, such as correlation, mean values, and variances of brightness is chosen as a measure of proximity. Such indicators add great computational complexity to the problem of image recognition and complicate the processes of obtaining information from a digital image.

In study [6], an informative assessment based on an index of digital image quality which does not require a basic copy or a supporting image was developed. Paper [7] is the development of the ideas of the previous work. It introduced three options for information assessment, all of which are based on image quality. The experiments conducted in the paper prove that estimates of informativeness are too subjective.

In article [8], in order to obtain a quantitative assessment, an attempt was made to formalize the concept of informativeness in terms of its usefulness and perception. In this work, an objective metric of a quantitative assessment of informativeness of combined images, based on the degree of preservation (distortion) of their distinguishing informa-

tion, consistent with visual perception, was developed. It should be noted that in the case when only one of the joined channels contains useful information, the complexing of images in multispectral systems can be harmful.

In paper [9], the problem of automation of the process of features' informativeness assessment in solving problems of computer vision problems was solved. The work created a system of criteria for assessing the informativeness of features to solve recognition problems in case of redundant features. But this work examines only spatial features.

It was proposed in [10] to use the adaptive method for recognizing homogeneous and heterogeneous textures based on the variability of their histogram ratings to process aerial imagery data. As a continuation of the research into the informativeness of digital images, the method for searching for suspicious objects [11] was developed and implemented as part of the on-board subsystem for the purpose of an unmanned aerial vehicle [11], which also uses assessments of the variability of aerial surveillance objects. The objective function of the method is to search for terrain objects that are found infrequently and stand out against the background of homogeneous textures. However, the issue of assessment of redundant informative saturation of digital images submitted for processing was not dealt with in the mentioned papers.

All this suggests that it is advisable to conduct a study dedicated to increasing the informativeness of a digital image.

## 3. The aim and objectives of the study

The aim of the study is to increase the informativeness of digital image data at a general decrease in content. This will make it possible to get a faster and more accurate result of object recognition.

To achieve the goal, the following tasks were set:

– to develop the information technology for determining redundant informativeness of a digital image;

– to apply the information technology for the calculation of redundant informativeness after preliminary smoothing images and scaling.

## 4. The study materials and methods

The mathematical statement of the problem of determining redundant informativeness of a digital image has the following form: let us assign a digital image $P = \left\{ p_{ij}, i = \overline{1, W}, j = \overline{1, H} \right\}$, where each pixel $p_{ij}$ is characterized by coordinates and by three colorful components. Introduce the metrics of informativeness of a digital image [12]:

$$MI = \left( 1 - \frac{I}{H * M} \right) * 100\%, \tag{1}$$

where $I = I^* + I^{**}$, $H$, $W$ are the linear dimensions,

$$I_{ij}^* = \begin{cases} 1, & p_{ij}^* \le \sigma_1, \\ 0, & p_{ij}^* > \sigma_1 \end{cases}$$

$$I_{ij}^* = \begin{cases} 1, & \left( p_{ij}^* \le \sigma_2 \right) \wedge \left( p_{ij}^* > \sigma_1 \right), \\ 0, & p_{ij}^* > \sigma_1, \end{cases}$$

$$I^* = \sum_i \sum_j I^*_{ij},$$

$$I^{**} = \sum_i \sum_j I^{**}_{ij},$$

$$A(P) = p^*,$$

$$A(A(P)) = p^{**},$$

$$A(P) = \sqrt{\Sigma_i^W \Sigma_i^H \left( p_{ij} - \overline{p} \right)^2}.$$

In these metrics, $\sigma_1$ and $\sigma_2$ act as certain (usually small) values of the variability of intensity of pixels in the local area with the center in the $(i, j)$-th pixel. The result of the calculation of such sliding variability in the formula is designated as $p^*$ – operator $A(P)$. If operator $A$ is overlaid on an image twice, the result will be designated as $p^{**}$ – operator $A(A(P))$.

For certainty in the future, we will imply that "variability" is the root mean square deviation of pixel intensity in some area. For example, if a sliding window for calculation of variability is taken as $(2n+1)\times(2n+1)$, variability in the local area with the center in the $(i, j)$-th pixel is determined as follows [13]:

$$S_{ij} = \sqrt{\frac{1}{n^2} \sum_{a=-n}^{n} \sum_{b=-n}^{n} \left( p_{i+a,j+b} - \overline{p}_{ij} \right)^2}, \quad (2)$$

where $\overline{p}_{ij} = \frac{1}{n^2} \sum_{a=-n}^{n} \sum_{b=-n}^{n} p_{i+a,j+b}.$

To understand the nature of the metrics of redundant informativeness, consider the image shown in Fig. 1. Most of the image is occupied by a forest and fields. This is uninformative information, while the basic information is carried by the "details". According to Shannon's entropy, unlikely events are most informative. In this case, similarly, "what is in abundance" in the photo (forest, fields) is uninformative. Informative is either "what is little", or what "stands out against the background of what is in abundance".



Fig. 1. The image of an area

As for how to evaluate "what is in abundance". In fact, this informal definition implies a homogeneous texture in the image. Homogeneous textures that occupy most of the photo (forest, fields) are uninformative. Local variability (1) was accepted as a way of highlighting such textures

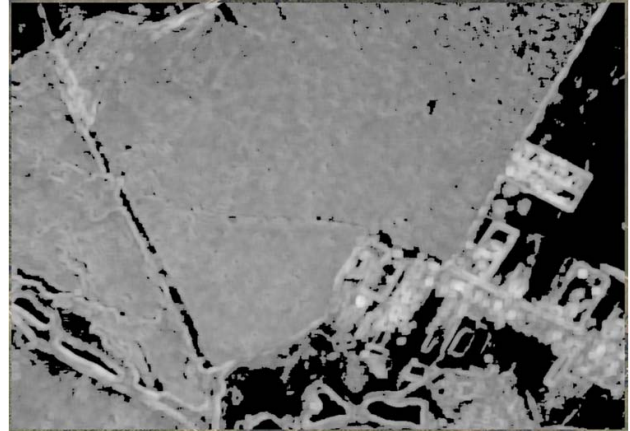(and in fact, as a way to segment an image into homogeneous areas), (Fig. 2).



Fig. 2. Result of processing image 1 with a sliding window of 15×15 with the calculation of variability $S_{ij}$

Fig. 2 shows that the forest represents a homogeneous area with approximately the same variability level. The same applies to the fields, but the variability level is lower, close to zero. In Fig. 2, the variability level from the smaller to the maximum one is determined by a change in color from black to white. The brightest areas are roads and buildings, as well as the forest and field boundaries. There are few such areas and, as mentioned above, they are the most informative areas. According to the metrics of redundant informativeness, part of the non-informative pixels is determined in Fig. 2, assigning a small variability level $\sigma_1$, for example, 7. All pixels that are less than this value in Fig. 2 will be considered uninformative. In this particular case, these will be fields and reservoirs.

For a more meaningful assessment of the metrics of redundant informativeness, consider the figure (Fig. 3). After processing by a sliding window with the calculation of variability, an area with a homogeneously variable forest in Fig. 2 now has a variability close to zero (because the local variability of locally variable textures is close to zero). In fact, this example shows that the areas of the original photo where there are textures with locally close variability are highlighted in black.
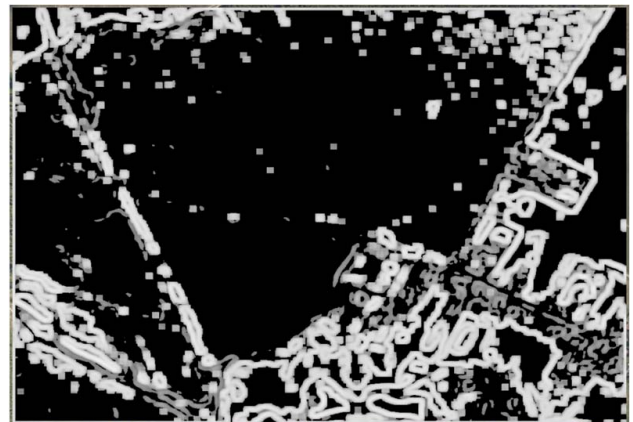


Fig. 3. The result of processing Fig. 2 by a sliding window of 15×15 with variability calculation
(double assessment of variability, photo 1)

These are uninformative pixels that were looked for. They are determined from metrics (1), assigning $\sigma_2$, which is close to 0. For example, for certainty $\sigma_2 = 7$ (in this case, 7 is "close to zero", because the pixel intensity varies from 0 to 255, from black to white, so 7 is rather "dark pixels").

## 5. Results of the studies of redundant informativeness of digital images after their preliminary processing

### 5. 1. Information technology for determining redundant informativeness of a digital image

The information system for evaluating redundant information of digital images was developed in the C# programming language, in the Microsoft Visual Studio 2019 (USA) environment.

Minimum system requirements:
– 64-bit operation system Windows;
– Microsoft .NET Framework 4.7;
– 67 KB of accessible space on a hard disk.

*Input data:* digital images of the following formats: JPEG (.jpg), BMP (.bmp), PNG (.png).

*Output data:* segmented digital images and estimates of image informativeness.

After reading an image from a file, the program converts it from a raster image to a set of three-dimensional points. Each point is described by the intensity of the components of each of the color channels. Next, it is possible to convert a color image to grayscale and apply pre-processing of digital images, namely the Gauss filter, JPEG lossy compression, and scaling.

Based on the sliding window, a convolution, in the center of which there is mean quadratic deviation of all pixels of the window, is implemented. The result is an image that must be normalized in the interval (0; 256). By re-implementing this convolution, it is possible to calculate the estimate of informativeness of a digital image based on the entered metrics.

The flow-chart of information technology for redundant information evaluation is shown in Fig. 4.

As a result, the information system provides an estimate of the redundant informativeness of a digital image after its pre-processing and segmentation.
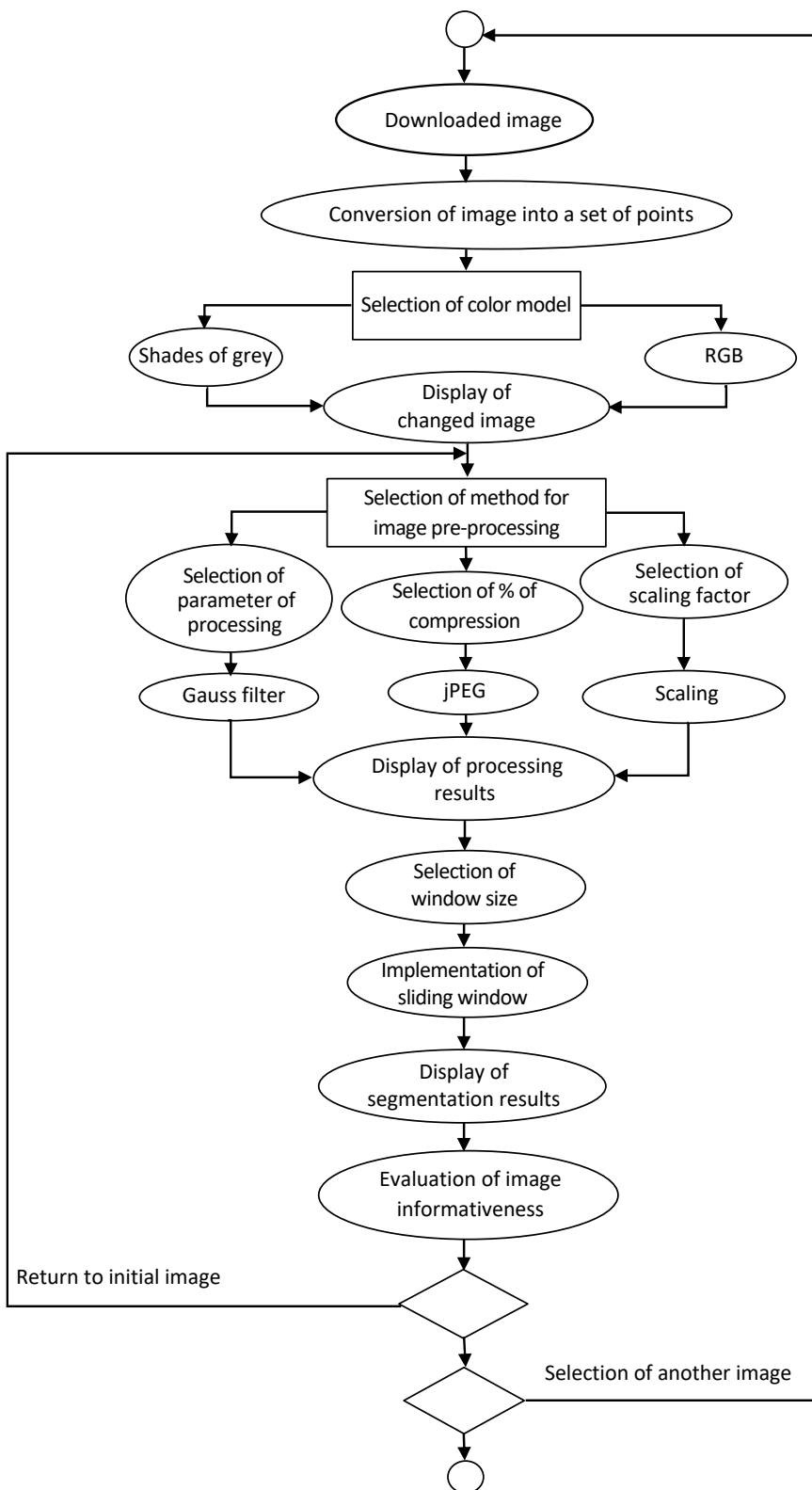


Fig. 4. Flowchart of the information system for a redundant information evaluation

### 5. 2. The use of information technology to study the estimate of redundant information content in a digital image

If we consider a digital image that has a lot of redundant information or background (for example, a forest or a field), we will not observe the data variability in these areas of the image, in other words, the variance will be constant. It is

advisable to apply the Gauss filtering method to such images with the parameter. The result of overlaying the image filter is on the right (Fig. 5).

To assess the redundant informativeness of the image, it is necessary to enter the value of the metric σ in the appropriate technology field (Fig. 6).

Several experiments were conducted to study the dependence of redundant informativeness of a digital image on parameter σ. Fig. 7 shows the result of applying the Gauss filter at σ=6 and the value of redundant informativeness.

Table 1 gives the estimates of informativeness of digital images obtained after overlaying the Gauss filter with different values of parameter σ.

Fig. 8 shows the plots of dependence of informativeness estimate on the value of parameter σ for each test.

Fig. 9 shows a digital image before and after changing its linear dimensions at a scaling factor of 0.8.



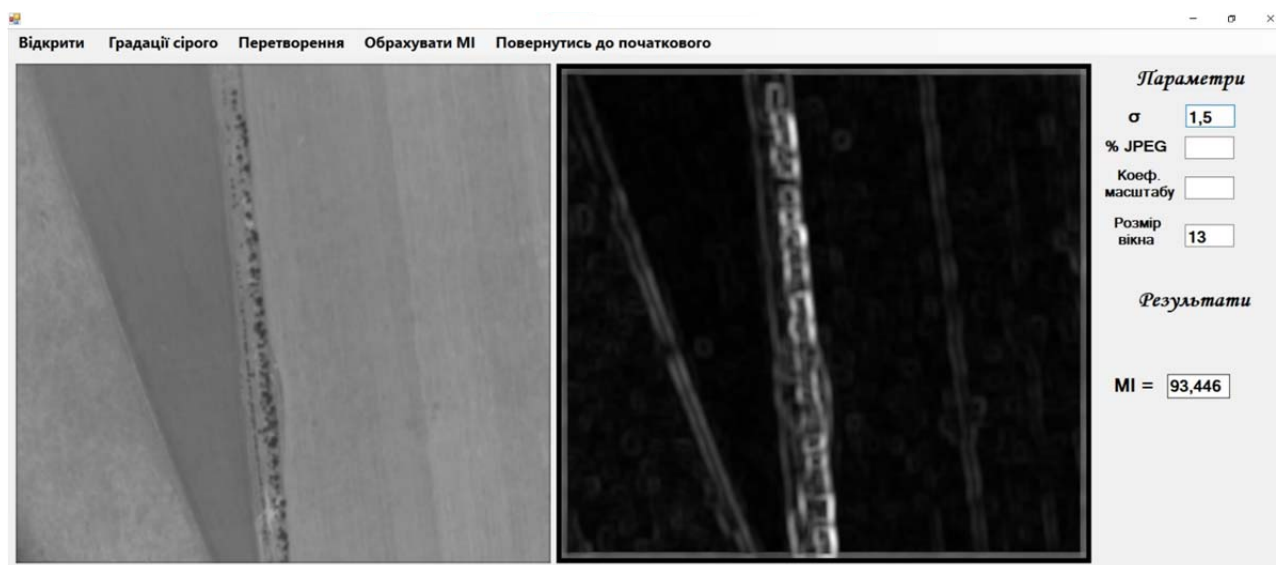Fig. 5. Using the Gauss filtering method with parameter σ=1.5



Fig. 6. Calculation of the image informativeness estimate

Table 1

Estimates of informativeness of digital images after overlaying the Gauss filter

| σ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| DI | 94.406 | 89.79 | 88.335 | 79.192 | 76.993 | 72.325 | 83.018 | 83.336 | 75.805 |
| 0,5 | 95.62 | 90.347 | 95.373 | 2.054 | 87.069 | 80.396 | 91.021 | 84.311 | 92.415 |
| 1 | 96.398 | 94.481 | 98.694 | 96.684 | 96.364 | 84.528 | 92.374 | 89.7 | 95.138 |
| 1,5 | 97.041 | 95.849 | 98.834 | 97.758 | 97.939 | 86.279 | 93.429 | 91.779 | 96.524 |
| 2 | 97.01 | 96.279 | 98.517 | 98.067 | 97.912 | 87.568 | 93.752 | 93.109 | 96.934 |

Continuation of Table 1

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|
| 2,5 | 97.076 | 97.125 | 98.258 | 98.088 | 98.038 | 88.699 | 94.267 | 93.838 | 97.123 |
| 3 | 96.908 | 97.266 | 97.916 | 97.868 | 97.67 | 89.556 | 94.407 | 94.594 | 96.978 |
| 3,5 | 96.662 | 97.362 | 97.54 | 97.492 | 97.541 | 90.351 | 94.724 | 95.044 | 96.961 |
| 4 | 96.546 | 97.082 | 97.194 | 97.188 | 97.163 | 91.255 | 94.828 | 95.403 | 96.807 |
| 4,5 | 96.318 | 96.93 | 96.814 | 96.771 | 96.382 | 92.351 | 95.029 | 95.603 | 96.651 |
| 5 | 96.359 | 96.546 | 96.455 | 96.461 | 96.596 | 93.438 | 95.084 | 95.774 | 96.415 |
| 5,5 | 96.155 | 96.257 | 96.121 | 96.069 | 96.322 | 94.577 | 95.169 | 95.847 | 96.112 |
| 6 | 95.883 | 95.879 | 95.728 | 95.745 | 95.928 | 95.192 | 95.15 | 95.486 | 95.841 |
| 6,5 | 95.569 | 95.585 | 95.438 | 95.39 | 95.658 | 95.317 | 95.124 | 95.182 | 95.465 |
| 7 | 95.211 | 95.238 | 95.058 | 95.068 | 95.308 | 95.03 | 94.974 | 94.789 | 95.19 |
| 7,5 | 94.917 | 94.955 | 94.8 | 94.733 | 95.048 | 94.793 | 94.968 | 94.47 | 94.836 |
| 8 | 94.632 | 94.638 | 94.449 | 94.45 | 94.735 | 94.447 | 94.659 | 94.143 | 94.542 |
| 8,5 | 94.313 | 94.35 | 94.17 | 94.13 | 94.471 | 94.177 | 94.541 | 93.819 | 94.288 |
| 9 | 94.089 | 94.095 | 93.91 | 93.872 | 94.216 | 93.894 | 94.342 | 93.515 | 94.01 |
| 9,5 | 93.82 | 93.821 | 93.569 | 93.577 | 93.949 | 93.638 | 94.062 | 93.218 | 93.755 |
| 10 | 93.616 | 93.589 | 93.403 | 93.323 | 93.718 | 93.365 | 93.86 | 92.919 | 93.525 |
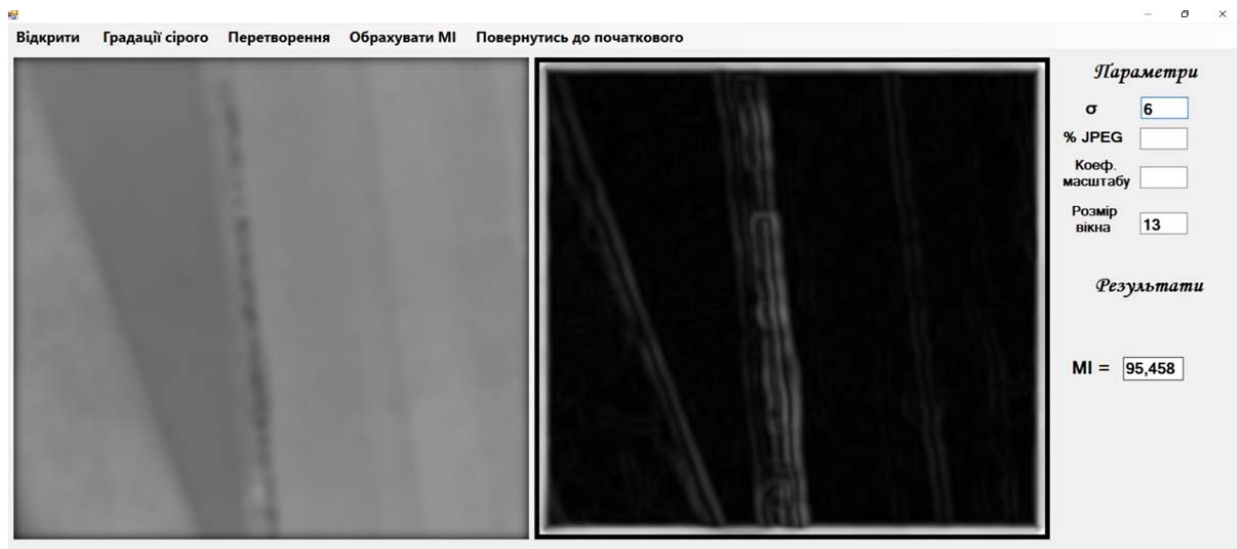


Fig. 7. Filtration by the Gauss method with parameter σ=6

After scaling using the information technology, an estimate of redundant informativeness of a digital image was determined (Fig. 10).

Several experiments were conducted to determine the dependence of the value of redundant informativeness of a digital image on its scaling factor. Fig. 11 shows the value of redundant informativeness at a scaling factor of 0.4.

Table 2 gives the estimates of informativeness of digital images, obtained depending on a change in linear dimensions of an image with different values of scaling factor:

Table 2

Estimates of informativeness of digital images with scaling factor values

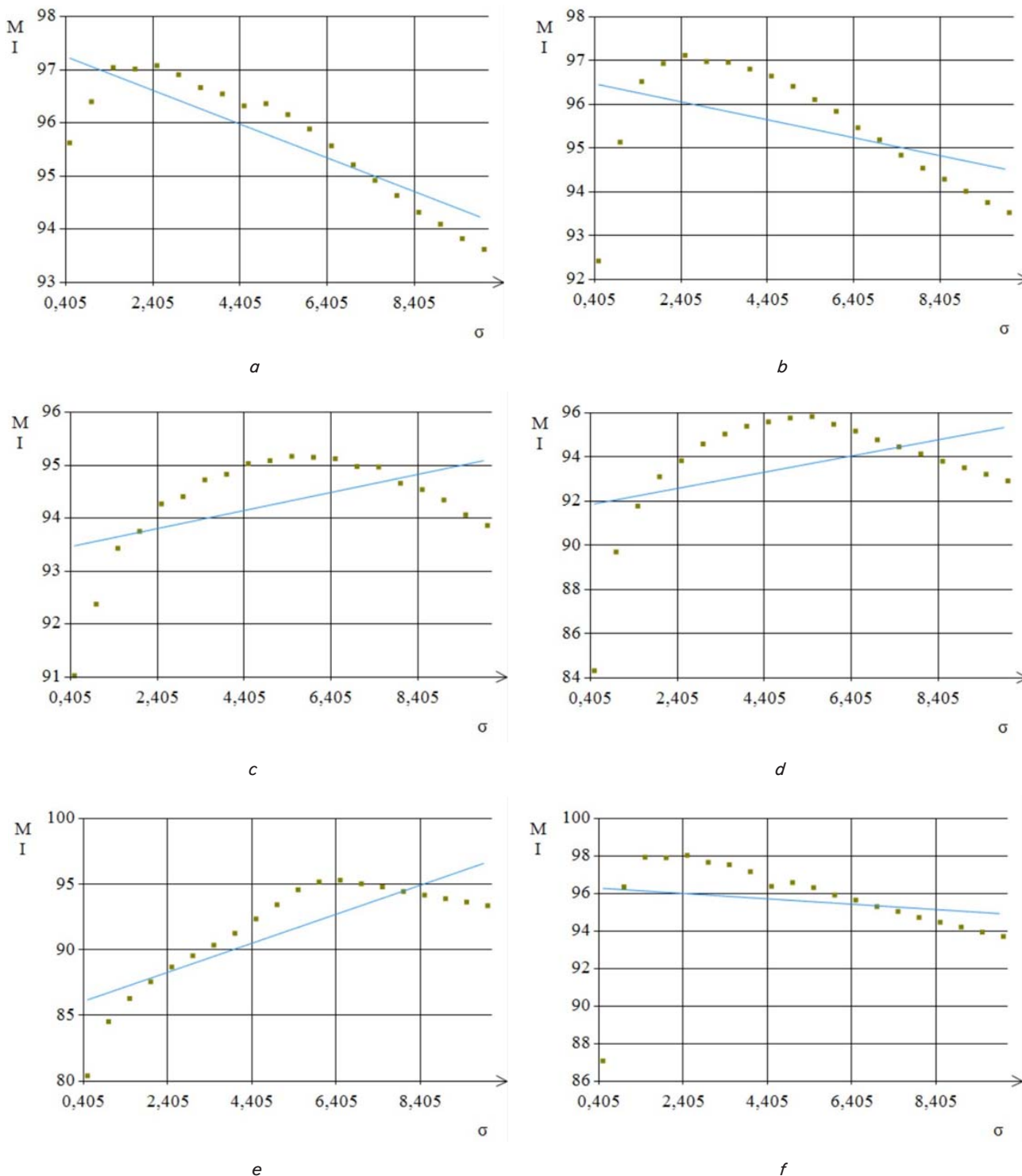| No | DI | Linear dimensions, scaling factor | | | |
|---|---|---|---|---|---|
| | | 0.2 | 0.4 | 0.6 | 0.8 |
| 1 | 78.985 | 48.94 | 68.46 | 76.341 | 82.45 |
| 2 | 78.183 | 74.855 | 80.646 | 81.214 | 82.055 |
| 3 | 88.335 | 81.73 | 86.919 | 88.689 | 89.591 |
| 4 | 79.192 | 67.295 | 75.152 | 78.637 | 80.308 |
| 5 | 49.377 | 52.554 | 52.012 | 50.1 | 48.721 |
| 6 | 72.325 | 95.655 | 87.739 | 82.232 | 79.654 |
| 7 | 83.018 | 88.763 | 87.45 | 87.448 | 87.12 |
| 8 | 83.336 | 98.138 | 91.334 | 89.031 | 87.641 |
| 9 | 85.601 | 99.521 | 97.66 | 94.411 | 91.778 |

Fig. 8. Dependence of the estimate of informativeness on the value of parameter σ: *a* — series of experiments No. 1; *b* — series of experiments No. 2; *c* — series of experiments No. 3; *d* — series of experiments No. 4; *e* — series of experiments No. 5; *f* — series of experiments No. 6

Fig. 12 shows the plots of the dependence of the value of redundant informativeness of a digital image on the value of the scaling factor for each test.

The information technology for determining redundant informativeness makes it possible to study the impact of applying the sliding window method to a digital image. The result of using the assigned image convolution and calculation of the estimate on the right is shown in Fig. 13.

To study the impact of the application of the sliding window method on redundant informativeness, the size of the sliding window with various parameters was changed (Fig. 14).

Table 3 gives the estimates of informativeness of digital images, obtained depending on the size of the sliding window to process the image with different values of scaling factor.

Fig. 9. Change of linear dimensions of an image with parameter a=0.8



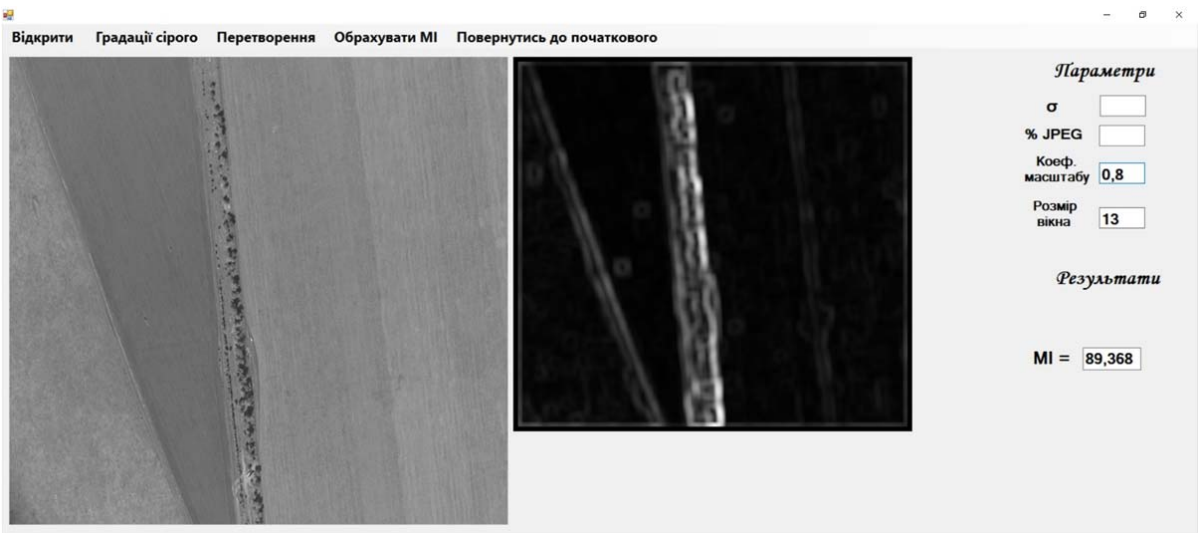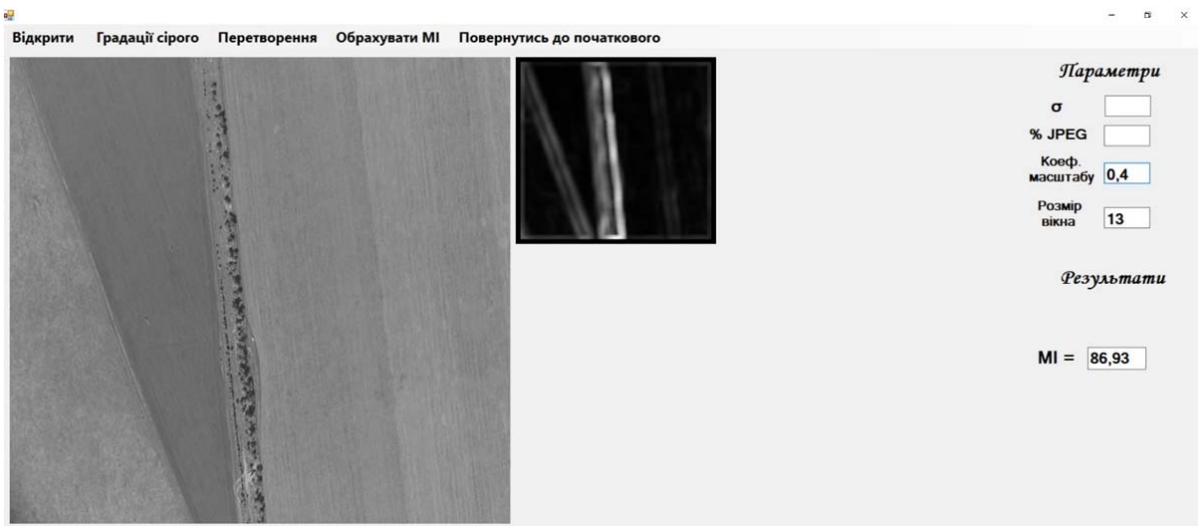Fig. 10. Calculation of the estimate of image informativeness



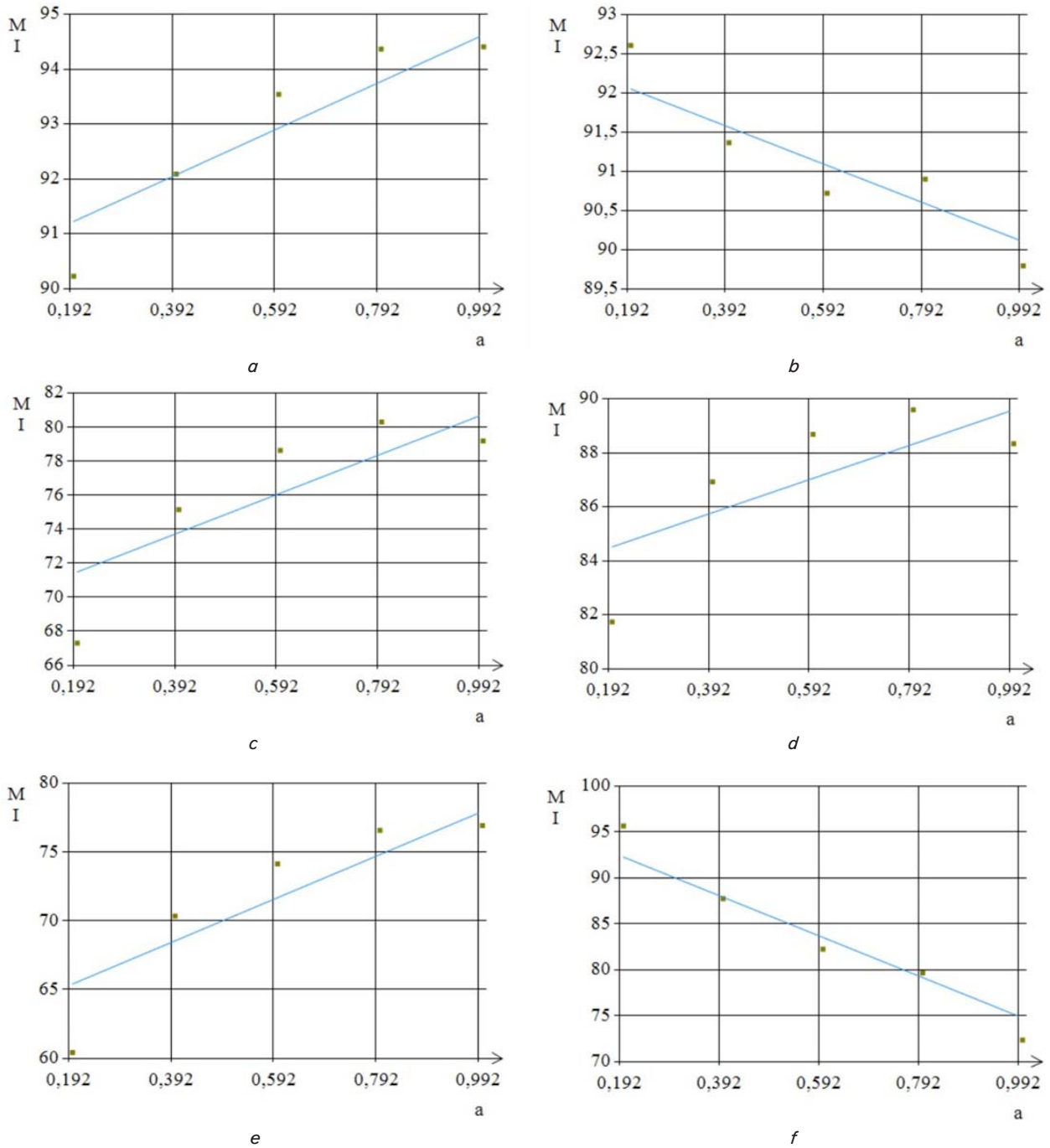Fig. 11. Change in linear dimensions of an image with parameter a=0.4

Fig. 12. Reproduction of the linear dependence of the informativeness estimate on parameter a:σ: *a* — series of experiments No. 1; *b* — series of experiments No. 2; *c* — series of experiments No. 3; *d* — series of experiments No. 4; *e* — series of experiments No. 5; *f* — series of experiments No. 6

Table 3

Estimates of informativeness of digital images depending on the size of the sliding window

| No | DI 13×13 | Sliding window, window size | | | |
|---|---|---|---|---|---|
| | | 3×3 | 7×7 | 11×11 | 17×17 |
| 1 | 2 | 3 | 4 | 5 | 6 |
| 1 | 94.406 | 97.527 | 95.999 | 94.912 | 93.402 |
| 2 | 89.79 | 94.826 | 92.14 | 90.419 | 88.8 |
| 3 | 88.335 | 93.334 | 90.673 | 88.976 | 87.048 |
| 4 | 79.192 | 91.835 | 84.792 | 80.741 | 76.421 |
| 5 | 76.933 | 91.033 | 83.097 | 78.597 | 74.118 |
| 6 | 72.325 | 86.88 | 77.391 | 73.649 | 70.07 |

Continuation of Table 3

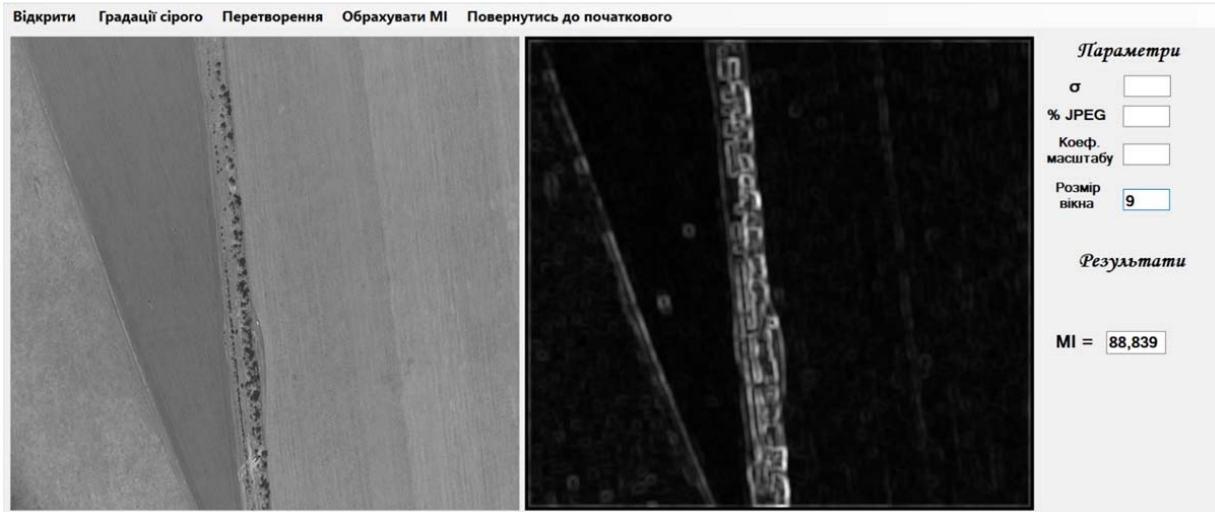| 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| 7 | 83.018 | 93.819 | 87.831 | 84.657 | 81.15 |
| 8 | 83.336 | 93.821 | 87.822 | 84.67 | 81.148 |
| 9 | 85.601 | 94.261 | 89.044 | 86.591 | 83.965 |
| 10 | 75.805 | 89.421 | 81.463 | 77.478 | 72.965 |



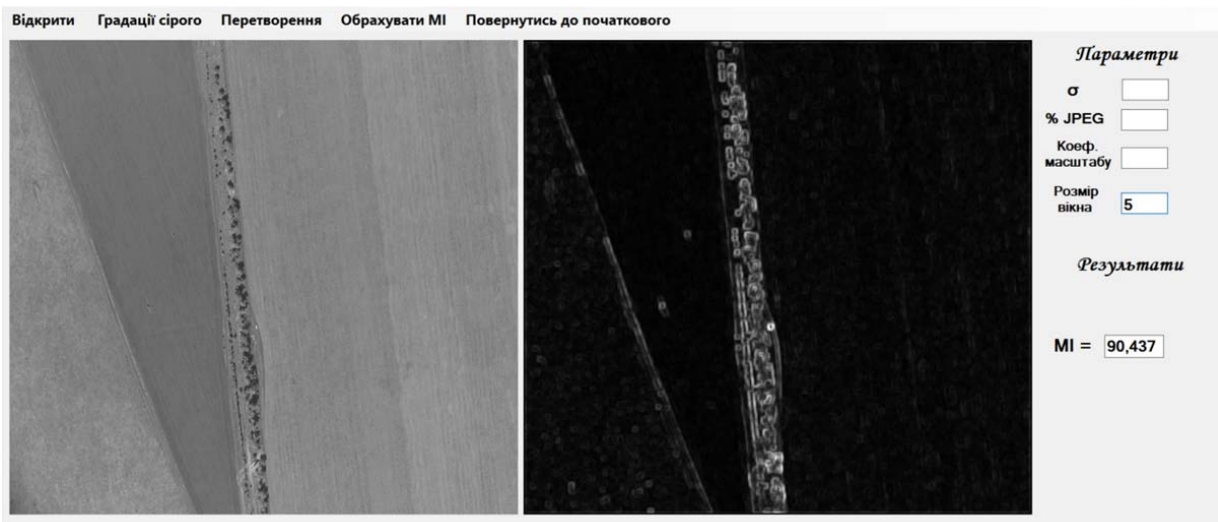Fig. 13. Change in dimensions of a sliding window for processing with parameter $n$=9



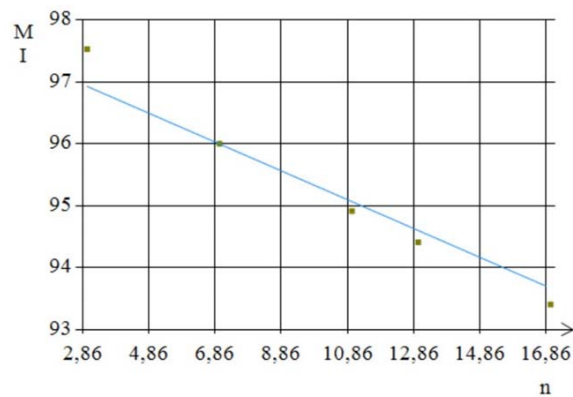Fig. 14. Implementation of a sliding window



Fig. 15. Linear dependence of the estimate of informativeness on parameter a

Fig. 15 shows the reproduction of linear dependence of the estimate of informativeness on parameter a.

As Fig. 5–15 and Tables 1, 2 demonstrate, application of Gauss filtering, scaling, selection of sliding window size, all the methods of digital image preprocessing, have an impact on the estimate of redundant informativeness.

## 6. Discussion of the results of using the information technology for assessment of redundant informativeness

The information technology provided an opportunity to evaluate the redundant informativeness of a digital image. The obtained results (Fig. 9, 13, 14) indicate that the application of preprocessing methods to an image affects the content of informativeness. These methods include the Gauss filter, JPEG lossy compression, and scaling.

As Fig. 9 shows, when using the Gauss filter, the informativeness estimate depends on the value of parameter σ: the higher parameter σ, the lower the value of redundant informativeness. After the experiments, it was concluded that with an increase in the values of this parameter, the percentage of redundant information decreases. Fig. 13 proves that it is possible to get an image with more informativeness by scaling it at a factor less than 1. This is explained by the smoothing effect due to reducing the impact of the high-frequency component of a digital image. But starting with some threshold, the estimate of information redundancy increases due to a strong blurring of an image.

The informativeness of a digital image can be increased by choosing the size of the sliding window. From Fig. 15, it is possible to draw conclusions that the smaller the size of the sliding window, the higher the informativeness.

The information technology for assessing the impact of redundant informativeness is limited to the use of only four methods of preprocessing digital images: the Gauss filter, JPEG lossy compression, and scaling.

In further studies, the authors aim to research the use of the introduced metrics (1) in the problems of automatic formation of educational datasets for convoluted neural networks as part of the technology of information filtration of visual information from digital images. The use of recurrent learning patterns that combine statistical unsupervised recognition methods and deep learning methods require these information filters to formalize data classes, which, among other things, are characterized by texture homogeneity.

## 7. Conclusions

1. The use of information technology for determining redundant informativeness proves that pre-smoothing of images or their scaling down contribute to the use of the proposed metrics of redundant informativeness. This is due to the fact that scaling down linear dimensions and anti-aliasing are both the operations that "suppress" the high-frequency component of a digital image, which to some extent affects its variability. This "suppression" aims to a great extent to "remove" random noises.

2. With the help of information technology for determining redundant informativeness, the impact of the magnitude of the mask of local variability calculation (the size of the local region) was studied. Here is also the analog of smoothing: the larger the local area, the "stronger" the impact of the high-frequency component is suppressed. The introduced metrics can be used in the development of automated systems for recognizing visual images, in particular aerial surveillance data. In particular, less computationally complex statistical methods of pre-segmentation of images (unsupervised recognition) make it possible to reject low-informative fragments and to submit the rest for processing with more costly supervised recognition methods. The assessment of informativeness of the specified data units is the area where the introduced metrics can be used (1).

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# DEVELOPMENT OF A WEED DETECTION SYSTEM USING MACHINE LEARNING AND NEURAL NETWORK ALGORITHMS

*The detection of weeds at the stages of cultivation is very important for detecting and preventing plant diseases and eliminating significant crop losses, and traditional methods of performing this process require large costs and human resources, in addition to exposing workers to the risk of contamination with harmful chemicals. To solve the above tasks, also in order to save herbicides and pesticides, to obtain environmentally friendly products, a program for detecting agricultural pests using the classical K-Nearest Neighbors, Random Forest and Decision Tree algorithms, as well as YOLOv5 neural network, is proposed. After analyzing the geographical areas of the country, from the images of the collected weeds, a proprietary database with more than 1000 images for each class was formed. A brief review of the researchers' scientific papers describing the methods they developed for identifying, classifying and discriminating weeds based on machine learning algorithms, convolutional neural networks and deep learning algorithms is given. As a result of the research, a weed detection system based on the YOLOv5 architecture was developed and quality estimates of the above algorithms were obtained. According to the results of the assessment, the accuracy of weed detection by the K-Nearest Neighbors, Random Forest and Decision Tree classifiers was 83.3 %, 87.5 %, and 80 %. Due to the fact that the images of weeds of each species differ in resolution and level of illumination, the results of the neural network have corresponding indicators in the intervals of 0.82–0.92 for each class. Quantitative results obtained on real data demonstrate that the proposed approach can provide good results in classifying low-resolution images of weeds*

*Keywords: agriculture, weeds, machine learning, YOLOv5, segmentation, Otsu's method, classification, algorithm evaluation*

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## 1. Introduction

The agricultural sector is one of the main branches of the economy of our country, since this industry annually provides 35–40 % of income to the state budget, and 15 % of the entire labor force of the country is employed in this sector. Weed control and monitoring of crop diseases have become an urgent task in the robotization of agriculture [1]. Monitoring of diseases and weeds at the stages of cultivation is very important for detecting and preventing diseases and eliminating significant crop losses, and traditional methods of performing this process require high costs and human resources, besides exposing workers to the risk of contamination with harmful chemicals. Therefore, the development of a pest control system that performs the detection and removal of weeds is the main area of research in the agricultural industry.

At the present time, the most optimal means for pest control is the large-scale use of herbicides, but the fact of uneven growth of weeds is not taken into account. As a result, crops also come under treatment with chemicals used to kill weeds, which can harm the environment. Previously used technologies could only distinguish between the presence or absence of plants, they were not capable of dividing them into weeds and agricultural crops. New technologies allow for more efficient spraying of herbicides, using them only in the right areas to preserve crops and protect the environment [2, 3]. The introduction of intelligent weed detection systems will also solve the problem of saving herbicides and pesticides, which are in demand means to combat plant diseases, various weeds and vectors of dangerous diseases in industrial agricultural production.

The use of autonomous robots and automated systems in agriculture can lead to a significant minimization of human efforts required to perform several agricultural tasks. To solve these problems, new classification systems have been proposed that can identify agricultural crops, distinguishing them from undesirable harmful vegetation [4, 5].