

Article

Identification, Recognition, and Classification of Micro-Objects Based on Signal-Point Characteristics of an Image

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Abstract

A problem was formulated, and methods and algorithms for identifying, recognizing, and classifying micro-objects were developed using problem-oriented image processing systems utilizing the characteristics of image structural components, dynamic models, and neural networks. The micro-objects studied were pollen grains and unicellular microorganisms, the application of which is in demand in palynology, environmental protection, ecology, and medicine. Models, algorithms, and software were developed based on the statistical, dynamic, morphometric, textural, and brightness characteristics of point image signals. The main contribution of the work is a hybrid model combining Daubechies wavelet functions (orders 4 and 8) with convolutional neural networks, which provides an average pollen grain recognition and classification accuracy of up to 97.7% and an overall classification accuracy of 98.2%. For comparative evaluation, the YOLO11m model was used as an independent baseline deep learning model, achieving 88.6% overall accuracy on a validation set of 280 images. The software includes tools for Gaussian filtering, median filtering, Sobel and Canny operators, and threshold correction of defective points with hard and soft control rules. The software package includes modules for training a convolutional neural network. The study was conducted on real-world databases of micro-object images for crop breeding and environmental pollution assessment.

Keywords: classification; correction; efficiency; filtering; image; identification; micro-objects; optimization; recognition; software package

MSC: 68T45; 68T07; 68T01; 68T05



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1. Introduction

The modern development of artificial intelligence and digital control systems significantly expands the possibilities of information processing in solving problems regarding the identification, recognition, and classification of images of micro-objects, the results of which are in high demand in the systems of palynology, environmental protection, ecology, agriculture, medicine, industry, and other fields of knowledge [1–4]. Traditional methods

of counting, analyzing microscopic samples, and manually processing their images based on computer vision systems (CVSs) are characterized by high labor intensity, subjectivity, and low accuracy of visualization results [5–7]. Of great scientific and practical significance is the research and development of methods and algorithms for identifying micro-objects based on problem-oriented image processing systems; for example, pollen grains, single-cell microscopic images, pictures of useful minerals, and others using tools of statistical, dynamic, morphometric, geometric, textural, color, brightness, and point-signal characteristics of micro-objects [8–10]. Micro-objects are characterized by small size, complex shape, significant variability of image points, and external influence variables, as well as the uniqueness of description models and their properties in the component structure [11,12].

The noted situations complicate the processes of identification, recognition, and classification of micro-objects, and at the same time determine the feasibility of maintaining systems for problem-oriented processing of image information in conditions of uneven illumination, noise, the presence of extraneous influences, blurring, shifts in points, complex background, and distortion of point signals and information [13–15]. The development of a system of problem-oriented information processing aimed at using dynamic, neural network (NN), and hybrid NN models in the identification, recognition, and classification of micro-objects is of great theoretical and practical interest. The system includes a set of algorithms for training neural networks with different architectures, and tools for translating classical algorithms into intelligent ones, which have the ability to adapt to variable conditions, as well as to achieve a significant reduction in the influence of defective points of distorted information. The system also demonstrates increased stability, high precision, and low-cost processing of image information compared to traditional systems based on the CVSs of micro-objects [16–18].

The main contributions of this work are as follows: a six-stage, domain-specific pipeline for preprocessing micro-object images is proposed, including normalization, segmentation, filtering, edge detection, and feature extraction; a hybrid model combining Daubechies wavelet functions (4th and 8th orders) with a convolutional neural network is developed for identifying, recognizing, and classifying micro-objects; tools for filtering and correcting defective image points based on Gaussian, median, Sobel operators, and hard/soft threshold correctors are implemented and compared; to improve the computational efficiency of micro-object identification, a multigrid approximation method with parallel computing on a GPU is applied; and the proposed system is evaluated on real-world datasets in various application areas, such as palynology, crop breeding, environmental monitoring, and medicine.

2. Related Works

In recent years, there has been a steady increase in scientific research interest in the identification, recognition, and classification of micro-objects using computer vision and artificial intelligence methods. A number of studies have focused on the development and improvement of methods for preprocessing images of micro-objects, including noise filtering, illumination correction, contrast normalization, and background distortion removal. Research has noted that complex backgrounds, impulse interference, blur, displacement, and the presence of foreign particles significantly impair the results of the identification, recognition, and classification of micro-objects [19–21].

They note the theoretical and practical significance of research aimed at developing methods and algorithms for classifying micro-objects based on neural networks (NNs) with various architectures. The effectiveness of NNs in classifying grain crop diseases, including wheat seed diseases, has been demonstrated using noisy data. In a comparative analysis of the performance of eight CNN architectures, the VGG19 and VGG16 models showed the

best results for pollen grain classification [22–25]. However, it should be noted that most existing studies focus primarily on the visual classification of pollen. They do not consider solutions to the problems of identifying, recognizing, and classifying micro-objects based on the dynamic, morphometric, textural, or brightness characteristics of the image [26,27].

Adaptive neural network learning algorithms are of considerable interest and are used for automated disease detection on the leaves of agricultural crops such as wheat and rice. A number of studies employ artificial intelligence methods based on the analysis of frequency and spectral characteristics of the cellular structures of plant seeds [28–30]. However, such approaches typically require expensive laboratory equipment and complex experimental conditions, which limits their practical applicability in large-scale and field studies.

Considerable attention is being paid to the use of computer vision technologies for the analysis of microscopic objects in medical and biological research, including the recognition of microorganisms and microbes in epidemiology. These studies utilize hardware and software systems, including digital and computer microscopes, automated imaging systems, and specialized software. RGB and HSV color models are widely used for analyzing micro-objects. These models calculate the parameters of color components (R, G, B), brightness (Y), hue (H), saturation (S), and value (V), which are used as features for subsequent classification. Methods and software tools have been proposed for extracting the statistical and morphological characteristics of images, such as mean values, variances, standard deviations, and minimum and maximum signal values [28–30].

Existing work provides a theoretical and practical foundation for further research. However, several important challenges remain. First, most existing studies primarily focus on visual or texture classification and do not integrate dynamic, morphometric, or luminance characteristics of image points into the preprocessing pipeline. Second, although deep learning models such as convolutional neural network (CNN)-based architectures have shown promising results, they are typically applied without domain-specific mathematical preprocessing, which reduces robustness to noisy or distorted images. Third, only a few studies propose a unified, domain-specific framework that simultaneously addresses the problems of defective point correction, edge-based feature extraction, and classification using neural networks. This paper addresses these gaps by proposing a hybrid model that combines Daubechies wavelet decomposition with a convolutional neural network supported by a six-stage preprocessing pipeline and GPU-accelerated multigrid approximation, achieving classification accuracy superior to the state-of-the-art results presented in the literature.

3. Materials and Methods

Mechanisms for preliminary information processing have been developed. At the design stage, solutions to problems of structural analysis, extraction, segmentation, interpretation, and filtering of contour points and fragments of the identified image of micro-objects are of great importance [31–33]. The technology of registration, counting, visualization, and systematization of images of micro-objects used in the systems of palynology, environmental protection and ecology, medicine, agriculture, and other fields of knowledge has been studied. A functional structure for problem-oriented processing of micro-object information for identification, recognition, and classification based on the characteristics of image structural components has been established. A subsystem for “Preprocessing images of micro-objects”, such as pollen grains, has been implemented, comprising six sequential stages. In the first stage, the micro-object image is normalized, with its points reduced to a size of 128×128 pixels in the range $[0,1]$, and relative ImageNet statistics are standardized. In the second stage, the region of interest of the image is segmented using a thresholding method and morphometric operations. The third stage involves filtering image points and

correcting defective contour points using Gaussian and median filters, as well as the M operator. In the fourth stage, micro-object boundaries are detected using the Sobel operator. The fifth stage extracts dynamic, morphometric, and textural characteristics, as well as corner points, spots, and edges from the image. At the sixth stage, the processed images are fed to the input of a neural network for identification, recognition, and classification of micro-objects into four morphological classes.

3.1. Tools for Optimizing Micro-Object Identification Processes Based on Characteristics in the Image Structure

The paper employs two complementary approaches. The primary contribution is a hybrid model combining Daubechies wavelet functions (orders 4 and 8) with a CNN for contour-based micro-object identification. The mathematical preprocessing pipeline—including dynamic time series decomposition, multigrid approximation, and spline interpolation—serves as the feature extraction stage, whose outputs are then fed into the neural network classifier. The YOLO11m model is used as an independent deep learning baseline for comparative evaluation. Problems concerning structural analysis, contour extraction, adaptive segmentation, and filtering of defective points in fragments of micro-object image contours have been solved [34–37]. Models, algorithms, and tools for problem-oriented information processing have been developed. The contour of the image of micro-objects is described by a sequence of points $X = \{x_t\}$, $t = 1, \dots, n$, and the x_t point of the contour at time t is considered as a dynamic random time series (RTS) [38,39].

Figure 1 shows representative samples from the experimental dataset for all four morphological classes (Corylus avellana normal, Corylus avellana abnormal, Alnus normal, and Debris), along with the corresponding preprocessing steps and model output. For each sample, the following are shown: the original input image (128×128 pixels), the normalized image (step 1), the Gaussian-filtered image (step 3), the Sobel boundary map (step 4), the Daubechies 4 wavelet approximation coefficients (step 5), the true class label, and the predicted class.

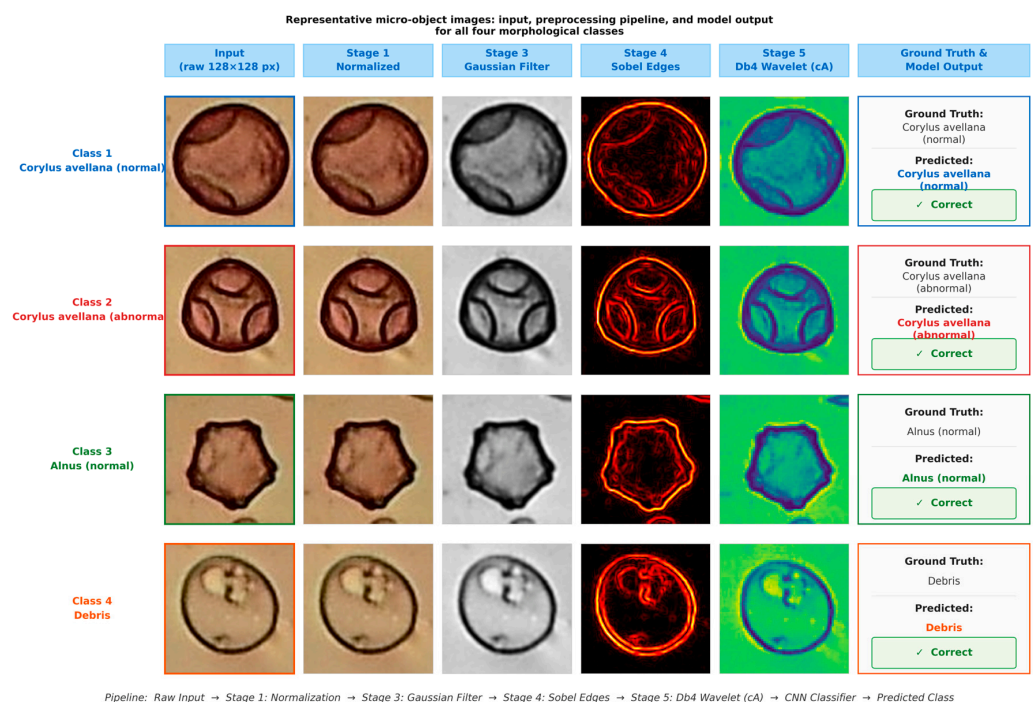


Figure 1. Representative images of micro-objects and preprocessing pipeline for four morphological classes.

The image contour is traversed clockwise, using a representation of the point sequence as a code chain, starting from a canonically defined starting point—namely, the point of maximum curvature on the contour. To ensure rotational invariance, the angular representation of the contour is calculated relative to the local tangent direction.

Scale invariance is achieved by normalizing points, parameterizing the contour length, and comparing it to a unit arc length. Invariance with respect to the choice of the starting point is guaranteed by anchoring the traversal to a geometrically stable reference point. Key issues addressed include tools for tracking, detection, and correction of “noise”, “interference”, removal of “foreign particles”, blurring, point shift, as well as distorted information and defective image points.

The key issues investigated are the methodology of tracking, detection, and correction of “noise”, “interference”, and shift in points, as well as distorted parts of information and defective points of the image. At the final stage of the problem-oriented system of information processing of micro-objects, decompositions of the RTS, transformations, and approximations (interpolations, extrapolations) are carried out. For this purpose, dynamic models were studied—polynomials, spline functions, Fourier transform functions, wavelet analysis, and filtering of low-frequency and high-frequency components of point-signal characteristics of the image [40,41].

An approach is proposed that utilizes hybrid identification models in the form of a linear and nonlinear function. The optimization functional for these models is defined as

$$y = (y_1, y_2, \dots, y_n) \rightarrow \min_{x \in X} \sum_{j=1}^n \|y_j - f_j(x_1, x_2, \dots, x_l)\|, \quad (1)$$

where $y_j = f_j(x_1, x_2, \dots, x_l)$, $j = \overline{1, n}$, and n —the number of approximating points of the image of micro-objects.

The results of the hybrid with NN Daubechies spline 4 for the minimum root-mean-square error of image point identification are estimated as

$$E = \frac{1}{n} \sqrt{\sum_{i=1}^n (y_i - y'_i)^2}, \quad (2)$$

where E —mean square error of identifying and processing information from image points of a single micro-object; n —number of approximated points of the image being considered; y_i —actual value of a point of the i image being considered; y'_i —calculated value of a point of the output i image.

Experimental values of the mean square error (MSE) were obtained using a dynamic Daubechies model, four classical neural networks, and a combination of a multilayer, loosely connected CNN for approximating a normalized image contour point, the size of which is specified in pixels. The results were averaged over 2896 pollen grain images included in a dataset for the breeding and seed production of grain crops.

Table 1 shows the specific parameters of two CNNs with the architectures used.

The quality of the NN is achieved by regulating the number of input n neurons, x_i , and synaptic weights w_i [42–44].

We will demonstrate image identification of micro-objects using a tool which uses a CNN. Neurons interact layer by layer in the network, and the network output for a particular case is considered as $j = 1 \dots 4$. Three output signals are produced, and the overall output is represented as [45,46]

$$y_j = f \left[\sum_{i=1}^n x_i \cdot w_{ij} + b_j \right], \quad (3)$$

where w_{ij} denotes the weights of inter-neuronal connections, x_i represents the synaptic coefficient of the neuron, and b_j is the neuron bias, which allows shifting the activation function independently of the input signals.

Table 1. CNN parameters.

Parameter	CNN Models	
	VGG16	VGG19
Convolutional layers	13, 3×3 filters, padding = same	16, 3×3 filters, padding = same
Fully connected layers	FC-4096 $\rightarrow$ FC-4096 $\rightarrow$ FC-4	FC-4096 $\rightarrow$ FC-4096 $\rightarrow$ FC-4
Neurons in the output layer	4 (by number of classes)	4 (by number of classes)
Activation (hidden layers)	ReLU	ReLU
Activation (output layer)	Softmax	Softmax
Pooling	MaxPooling 2×2	MaxPooling 2×2
Dropout	0.4 (phase 1)/0.3 (phase 2)	0.4 (phase 1)/0.3 (phase 2)
Total parameters	~138 million	~144 million

The activation function of the output layer Softmax provides the output of the NN, and is interpreted as the value of the probability function of membership in each class:

$$\hat{y}_j = \text{softmax}(y_j) = \frac{e^{y_j}}{\sum_{k=1}^4 e^{y_k}}, \quad j = \overline{1, 4}. \quad (4)$$

Note that the bias of b_j allows the neuron to activate even with zero input values, thereby increasing the flexibility and generalization ability of the network learning model.

Note that the variable indicates the magnitude of the bias. Including it in Formula (3) is a common practice when constructing neural networks. The presented model (3) enables neuron activation even when all input signals x_i are zero. Furthermore, bias b_j is initialized to zero at the beginning of training and is automatically optimized during network training, shifting the activation function relative to the input signals. This significantly increases the flexibility and generalization ability of the neural network, allowing for the testing of a micro-object classification tool based on four morphological classes of pollen grains: *Corylus avellana* (well-developed), *Corylus avellana* (abnormal), *Alnus* (well-developed), and Debris. The neural network's output layer contains four neurons.

The back propagation algorithm is used, which updates the value of b_j at each step of network training according to the gradient descent rule $b_j^{(t+1)} = b_j^{(t)} - \eta \cdot \frac{\partial L}{\partial b_j}$, where η —learning speed, L —loss function, and $\frac{\partial L}{\partial b_j}$ —partial derivative function that is determined depending on the magnitude of the displacement b_j .

For optimization, the AdamW algorithm [47] was used, allowing for adjustment of the network learning rate at each step.

The AdamW optimizer operates at the global learning level and adaptively scales the learning rate using estimates of the first and second moments of the gradient. To eliminate ambiguity, the following variable derivation technique is added to the full AdamW update equations: average value $m_t = \beta_1 m_{t-1} + (1 - \beta_1) \nabla L(w_t)$ —1st moment; variance $v_t = \beta_2 v_{t-1} + (1 - \beta_2) [\nabla_w L(w_t)]^2$ —2nd moment; correction bias $\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$, $\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$, where $\nabla_w L(w_t)$ is the gradient of the loss function with respect to w_t ; $\beta_1 = 0.9$ is the coefficient of the first moment, $\beta_2 = 0.999$ is the coefficient of the second moment, and $\varepsilon = 10^{-8}$ is a number introduced to ensure numerical stability.

The basic update rule of AdamW is given by

$$w_{t+1} = w_t - \alpha \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \varepsilon} - \alpha \cdot \lambda \cdot w_t, \quad (5)$$

where α is the learning rate, λ is the weight decay coefficients, and t is the iteration step number.

In this case, variable b_j ensures more stable and rapid convergence of the neural network model. It was determined that the tested hybrid model provides highly accurate approximation of image points and improves the network's ability to generalize to new data.

To calculate the values of the gradient loss function $\frac{\partial L}{\partial b_j}$ for all network parameters, the backpropagation algorithm was used. The calculated gradients are passed to the Adam optimizer, which performs adaptive weight updates using probability estimates $\beta_1 = 0.9$ and the second $\beta_2 = 0.999$ gradient moments. The learning rate in the first phase was $\eta = 0.001$, and fine-tuning was performed in the second phase with $\eta = 0.0001$ ($\text{min_lr} = \text{lr}/10$). Batch sizes were 32 (VGG16) and 16 (VGG19). Training was performed for 20 epochs in each phase with early stopping (patience = 6).

The weight of each neuron and its inter-neuronal connections, w_{ij} , is determined by the synapse x_i . The inter-neuronal connections of the first network layer are reduced to a matrix W , which for the network layer $w_{ij}(t + 1)$ is determined as

$$w_{ij}(t + 1) = w_{ij}(t) + v \cdot \delta \cdot x_i, \quad (6)$$

where $w_{ij}(t)$ —weight value of the i -th neuron in the j -th layer of the network; $t, t + 1$ —indices of network training time in the current and next iterations of the algorithm, respectively; v —designation of the network learning speed, $v > 0$; $\delta = Y_I - Y$ —the deviation of the value of the identified (approximated) Y point of the image from the value of point Y_I —the reference (modal) example at the network output.

If the difference δ is greater than the required value, the neuron weights in the network layer in question will be increased, reducing the network training algorithm's error.

Conversely, if the difference δ is less than the required value, the neuron weights in the network layer are decreased.

The characteristic parameters of the calculated output Y are adjusted until the minimum network training error is achieved.

To test the implemented identification tool, four types of pollen grains were used, represented by a sequence of multifocal images. Two networks were used in the study: the first, a VGG16 network, and the second, a VGG19 network, both with deep learning algorithms. Both models were trained using two-phase transfer learning based on ImageNet weights. In the first phase, only the classification block was trained (20 epochs), and in the second, the entire network was fine-tuned (20 epochs, $\text{min_lr} = \text{lr}/10$). Adam was used as the optimizer, with parameters $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 1 \times 10^{-7}$. The input image size was 128×128 pixels. To prevent overfitting, label smoothing (0.1), dropout (0.4/0.3), and early stopping (patience = 6) were applied. The optimal values of batch size and learning rate were determined by grid enumeration: $\text{batch_size} \{16, 32, 64\}$, $\text{lr} \{0.01, 0.001, 0.0001\}$.

Data augmentation tools and network filtering layers were used to retrain the networks during training.

The following data augmentation tools were used during training of the YOLO11m model: horizontal flip $p = 0.5$, random rotation in the range of $\pm 15^\circ$, random shift in the range of ± 0.05 , scaling in the range of $[0.5, 1.5]$, random HSV color space shift in hue ± 0.015 , saturation ± 0.7 , brightness ± 0.4 , random erasure of regions $p = 0.4$, mosaic augmentation $p = 1.0$, and the RandAugment automation tool. The input image size was 224×224 pixels. Training was performed over 70 epochs using the AdamW optimizer, an initial learning rate of $\text{lr}_0 = 10^{-5}$, cosine decay to $\text{lrf} = 0.01$, a batch size of 32, and dropout regularization of $p = 0.2$.

The tools for filtering point signals of images of micro-objects based on the use of Gaussian operators, median transform, Sobel, and threshold correction of distorted point signals are investigated [48,49].

The image filtering operator M is applied to each micro-object image and produces a response for every image point within the testing neighborhood $T = [-1, 1]$. For each image, n denotes the total number of point outcomes evaluated within this neighborhood. Background points are registered with a response value of $+1$, while false detections are assigned a value of -1 .

Let us present the complete scheme of coding the response of the M-filter, which forms a response for each image point in the neighborhood of $T = [-1, 1]$ according to the following rules:

$$M(x) = \begin{cases} +1, & \text{if the point belong to the background;} \\ -1, & \text{if the point is false detection;} \\ 0, & \text{if the point belong to the contour of a micro-object;} \\ c_k, & \text{if the point classified as a micro-object of class } k, \end{cases} \quad (7)$$

where $c_k \in \{1, 2, 3, 4\}$ are the labels of points belonging to the contour or interior region of a micro-object for the corresponding class.

This coding scheme enables the simultaneous filtering of defective points and classification of micro-objects in a single operator. Points belonging to genuine micro-objects are coded with the label of the corresponding class $c_k \in \{1, 2, 3, 4\}$, which allows for the combination of filtering defective points and classifying micro-objects within a single operator.

Figure 2 shows the graphical distribution of the NN response values. The vertical axis M denotes the number of NN response instances (frequency value) recorded in the micro-object image dataset. The horizontal axis T represents the response threshold in the range $[-2, 2]$, which defines the decision boundary for classifying image points as background ($+1$), false detection (-1), true micro-object contour (0), or a specific micro-object class ($c_k \in \{1, 2, 3, 4\}$). The two curves correspond to two overlapping NN response distributions: the $-I$ curve represents responses near the false detection threshold, and the I curve represents responses near the true micro-object detection threshold.

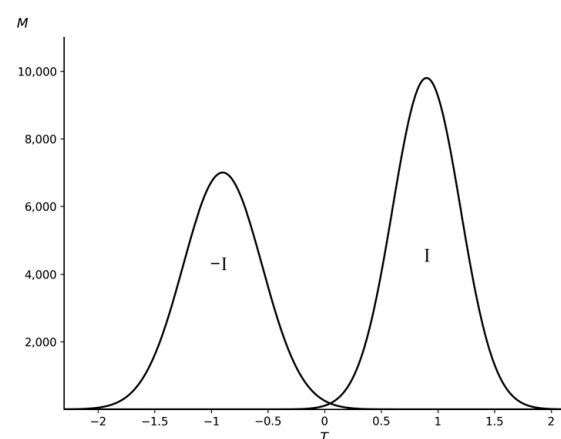


Figure 2. Graphical distribution of the NN responses.

Experimental studies of the hybrid NN model were conducted using training and test sets. The test set also includes the background portion of the micro-object image. Table 2 compares the values of the mean square error of the studied tools for filtering and correcting defective points of the image of micro-objects.

Table 2. Comparison of the values of the root-mean-square error of the tools for filtering and correcting defective points of images of micro-objects.

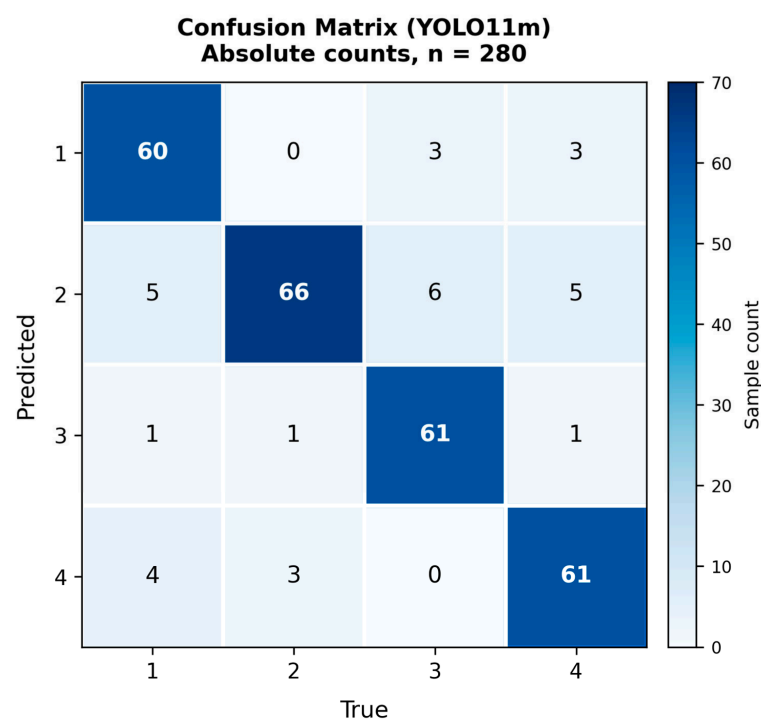
Filter	Accuracy		
	Signal/Noise	CVS	Hybrid
Gaussian	24.07	0.81	97.3
Median	26.86	0.92	98.2
Sobel	27.25	0.92	98.4
Threshold:			
Hard	28.95	0.94	98.7
Soft	28.56	0.93	98.8

The effectiveness of the implemented hybrid dynamic model of Daubechies 4 and a CNN on sets of medical micro-objects was studied. The tools of the hybrid CNN and Daubechies 8 models were also tested. Furthermore, the hybrid model for micro-object image identification is combined with the following tools:

- Parallel computing, adaptive neural network training, variable tuning;
- Reduction in uninformative points, normalization of grayscale images;
- Color image edge detection, texture, brightness representation, and other characteristics.

Algorithms for correcting defective points in micro-object images based on “soft” and “hard” thresholds were investigated. Analysis of the comparison results showed that the tool with a soft threshold for checking defective points in the image exhibits better visual characteristics than the tool with a hard threshold. The superior performance of the tools is evident when intermittent points appear, i.e., when unfavorable events occur during micro-object identification.

Figure 3 demonstrates the study’s results, which are confirmed by the YOLO11m model’s 88.6% classification accuracy, using a validation set containing four pollen classes. The horizontal axis (True) indicates the true object classes, and the vertical axis (Predicted) indicates the classes predicted by the model.

**Figure 3.** Classification of micro-objects based on YOLO11m and the error matrix.

The values on the main diagonal correspond to correctly classified samples: Class 1—60 samples, Class 2—66, Class 3—61, Class 4—61. Off-diagonal values indicate misclassifications: the largest number of errors is observed in Class 2, where five samples were misclassified as Class 1, six as Class 3, and five as Class 4. Classes 3 and 4 demonstrate the lowest inter-class errors (no more than 1–3 samples). The “background” row and column remain empty, indicating the absence of false positives for background objects. The total number of correctly classified samples was 248 out of 280.

Figure 4 illustrates the results of the YOLO11m model based on the normalized confusion matrix. The proportion of each true sample class is expressed, allowing for objective comparison of classes with different numbers of samples.

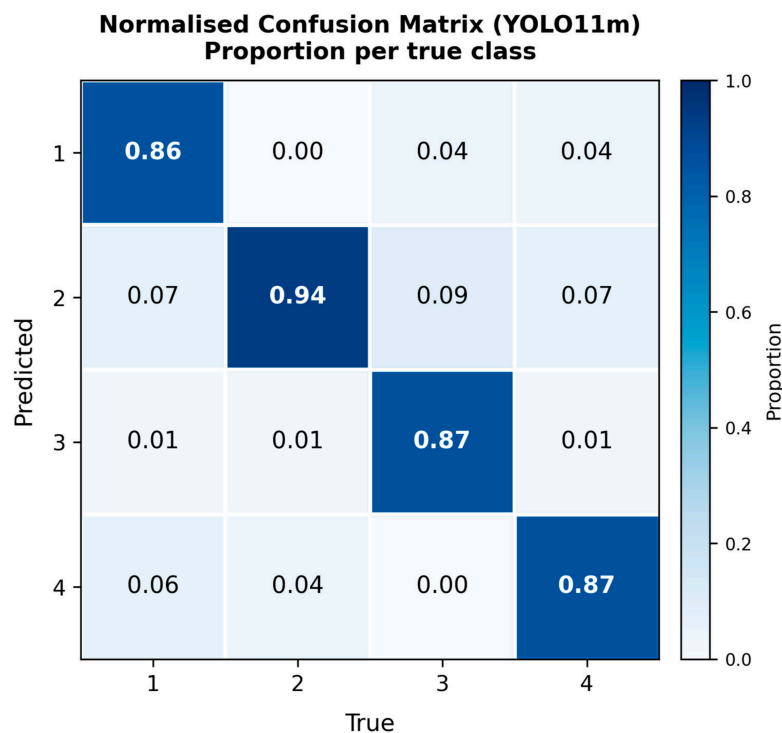


Figure 4. Classification based on YOLO11m and normalized confusion matrix.

The numbers of classified micro-objects on the training set are compared with the results obtained on the validation and test sets.

It was determined that the normalized confusion matrix represents the same classification results according to YOLO11m (Figure 2), with the numbers corresponding to the main diagonal. The proportions of correctly classified samples are shown: Class 1—0.86, Class 2—0.94, Class 3—0.87, and Class 4—0.87.

The highest number of errors is observed in Class 2, where 7% of micro-objects were incorrectly assigned to Class 1, 9% to Class 3, and 7% to Class 4. Moreover, the figure demonstrates the visual similarity of this class to the others.

Classes 3 and 4 are characterized by the result of a highly stable network mode. Moreover, the proportion of inter-class errors does not exceed 1–6%. The average classification accuracy was 88.5%. None of the classes fell below the 86% threshold.

Note that the difference between the two values is 88.6%, which is the overall accuracy of image point classification (Overall Accuracy). The result is obtained as the ratio of the number of correctly classified objects to the total number of objects included in the test set:

$$\text{Overall_Accuracy} = \frac{\sum_{i=1}^4 TP_i}{N_{\text{total}}} = \frac{60 + 66 + 61 + 61}{280} = \frac{248}{280} \approx 88.6\%. \quad (8)$$

The second value, 88.5%, is the macro-averaged accuracy, which is defined as the arithmetic mean of the accuracies for each class separately:

$$\text{Macro_Accuracy} = \frac{1}{4} \sum_{i=1}^4 \frac{TP_i}{N_i} = \frac{90.9 + 80.5 + 95.3 + 89.7}{4} \approx 88.5\%, \quad (9)$$

where N_i is the number of true objects of the i -th class.

Note that the difference between the two metrics is due to a slight imbalance in the number of objects in the test set's classes (from 64 to 82 objects per class). For balanced classes, both values are the same.

3.2. Micro-Object Image Identification Tools Based on Parallel Computing on GPU Graphics Adapters

The effectiveness of the cascade multigrid method was studied based on the criterion of computational complexity $O(N \ln \varepsilon^{-1})$, where N —total image size, and ε —approximation error of contour control points. Acceleration of calculations is ensured by the use of shared memory sharing tools, a cyclic multigrid operator, and the NVIDIA platform graphics processor.

A two-dimensional microscopic image of a micro-object is represented as a discrete brightness function $U(x_1, x_2)$, defined on a uniform grid of pixels. To apply the elliptic operator (11), the image is transformed into a three-dimensional representation as follows: the x_1, x_2 axes are the spatial coordinates of the image pixels (horizontal and vertical), and the x_3 axis is the pixel intensity brightness value normalized to the range $[0,1]$. The model of a two-dimensional image of a micro-object is defined by the size $M \times N$ pixels and is mapped into a three-dimensional cubic region $\Omega_h \in [1, \dots, M; 1, \dots, N; 1, \dots, K]$, where K is the number of brightness quantization levels.

The elliptic operator L is applied to the function $U(x_1, x_2, x_3)$ to describe the smoothness and connectivity of the contour points of the micro-object in the extended feature space. Boundary conditions $\partial\Omega_{h0}(U) = U_0$ and $\partial\Omega_{h1}(U) = \frac{\partial U}{\partial n_{h0}}$ define the brightness values at the image boundary and the normal derivative along the contour, respectively. The $2D \rightarrow 3D$ transformation is written as:

$$U : (x_1, x_2) \mapsto (x_1, x_2, x_3), x_3 = I(x_1, x_2), \quad (10)$$

where $I(x_1, x_2)$ is the normalized pixel intensity at point (x_1, x_2) .

A tool has been developed that performs a two-dimensional transformation of a microscopic image of size $M \times N$ pixels into a three-dimensional image. This involves introducing a third coordinate for point $x_3 = I(x_1, x_2)$, which corresponds to the normalized luminance intensity.

As a result, a cubic region Ω_h is formed, to which the elliptic operator (11) is applied. The proposed approach takes into account not only the spatial arrangement of contour points, but also their photometric characteristics in a single mathematical description.

A convex cube Ω_h is considered, which is represented as

$$L_h U_h = F_h \text{ in } \Omega_h, \Omega_h \in R^3, \partial\Omega_{h0}(U) = U_0, \partial\Omega_{h1}(U) = \frac{\partial U}{\partial n_{\partial\Omega}}, \quad (11)$$

where L —elliptic operator of the form $LU = \sum_{i,j} \frac{\partial}{\partial x_i} \left(a_{ij} \frac{\partial U}{\partial x_j} \right)$; a_{ij} —the ellipticity condition $a_{ij} = a_{ji}$; $\alpha > 0$ is such a constant that the condition $\sum a_{ij} \xi_i \xi_j \geq \alpha \sum \xi_i^2$, $\xi \in R^3$ and $i, j \in [1, 2, 3]$ is satisfied; F —known function; U —an unknown function that belongs to C^2 ; h —index indicating the point's belonging to the grid space; M, N, K —the problem dimension in R^3 . $\Delta h_j = \frac{1}{X_j}$; $X_j = \{M, N, K\}$; and $j \in [1, 2, 3]$ —sides of a cube.

Three-point and five-point finite-difference patterns of differential and elliptic operators are applied [50,51]:

$$L_h^*(\lambda) = \sum_{j=1}^3 \frac{(\lambda_{i+1} - 2\lambda_i + \lambda_{i-1})_j}{(\Delta h)_j^2} + 0(\Delta h^2); \quad (12)$$

$$L_h^{**}(\lambda) = \sum_{j=1}^3 \frac{(-\lambda_{i+2} + 16\lambda_{i+1} - 30\lambda_i + 16\lambda_{i-1} - \lambda_{i-2})_j}{(12\Delta h)_j^2} + 0(\Delta h^4). \quad (13)$$

The side of the cube on each grid has the following sequence: $\Delta h_i \leftarrow 2\Delta h_i \leftarrow 4\Delta h_i \leftarrow \dots \leftarrow q\Delta h_i$, where q —grid level defined as $q = 1, 2, 4, \dots, 2n$, $n \in N$.

The method was tested in two stages. In the first stage, problem (11) was solved using approximation tool L of type (12) or (13) on grid S_i until its error became less than the energy norm. In the second stage, the problem of replacing the coarse grid with a finer one was solved.

At the first stage of solving the problem, Jacobi and Gauss–Seidel approximate calculation tools were applied, and optimizations were tested based on conjugate gradients, which have the properties of smoothing high-frequency components of the image function U .

At the second stage of solving the image identification problems, the tools of interpolation basis-spline functions of Daubechies and algebraic orthogonal polynomials 4 and 8 were used.

Identification options based on the synthesis of Gauss–Seidel, conjugate gradients, and overrelaxation methods for signal characteristics were investigated. The results are evaluated based on the values of the winning coefficient, measured as the ratio of the approximation error at the output of models (12) and (13) with a level q grid function to the values of the output error obtained with bilinear interpolation using the operator for replacing the grid function I from level q with a level $q - 1$ grid function.

Operator I of bilinear interpolation $U_h^q \xrightarrow{I} U_{i,j,k}^{q-1}$, $U_h^q \in S_q$, $U_h^{q-1} \in S_{q-1}$ are used in the form:

$$\begin{aligned} U_{i,j,k}^{q-1} &= U_{i,j,k}^q, \quad U_{i\pm 1/2,j,k}^{q-1} = \frac{1}{2}(U_{i,j,k}^q + U_{i\pm 1,j,k}^q); \quad U_{i\pm 1/2,j\pm 1/2,k}^{q-1} = \frac{1}{4}(U_{i,j,k}^q + U_{i\pm 1,j,k}^q + U_{i,j\pm 1,k}^q + U_{i\pm 1,j\pm 1,k}^q); \\ U_{i\pm 1/2,j\pm 1/2,k\pm 1/2}^{q-1} &= \frac{1}{8}(U_{i,j,k}^q + U_{i\pm 1,j,k}^q + U_{i,j\pm 1,k}^q + U_{i\pm 1,j\pm 1,k}^q + U_{i,j,k\pm 1}^q + U_{i\pm 1,j,k\pm 1}^q + U_{i,j\pm 1,k\pm 1}^q + U_{i\pm 1,j\pm 1,k\pm 1}^q). \end{aligned} \quad (14)$$

Here, $i = 1, \dots, M$, $j = 1, \dots, N$ —index along the horizontal and vertical spatial axes of the image; $k = 1, \dots, K$ —index along the brightness quantization axis; q —current grid level, defined as $q = 1, 2, 4, \dots, 2^n$, $n \in N$; $q - 1$ —the next coarser grid level; $U_{i,j,k}^q$ —value of the grid function U at node (i, j, k) on grid level q ; and $U_{i\pm 1/2,j\pm 1/2,k\pm 1/2}^{q-1}$ —interpolated values at half-integer nodes between adjacent grid points, obtained via bilinear interpolation from the coarser grid level $q - 1$.

The experimental one-point bilinear interpolation can be written as

$$\begin{aligned} U_{i,j,k}^{q-1} &= \frac{1}{24}(12U_{i,j,k}^q + U_{i+1,j+1,k}^q + U_{i+1,j-1,k}^q + U_{i-1,j-1,k}^q + U_{i-1,j+1,k}^q + U_{i+1,j,k+1}^q + U_{i+1,j,k-1}^q + \\ &+ U_{i-1,j,k-1}^q + U_{i-1,j,k+1}^q + U_{i,j+1,k+1}^q + U_{i,j+1,k-1}^q + U_{i,j-1,k-1}^q + U_{i,j-1,k+1}^q). \end{aligned} \quad (15)$$

Figure 5a,b show graphs of the gain coefficient in the accuracy of micro-object identification based on a CNN, Daubechies 4 and 8 models, and tools for filtering and correcting defective points and distorted image information.

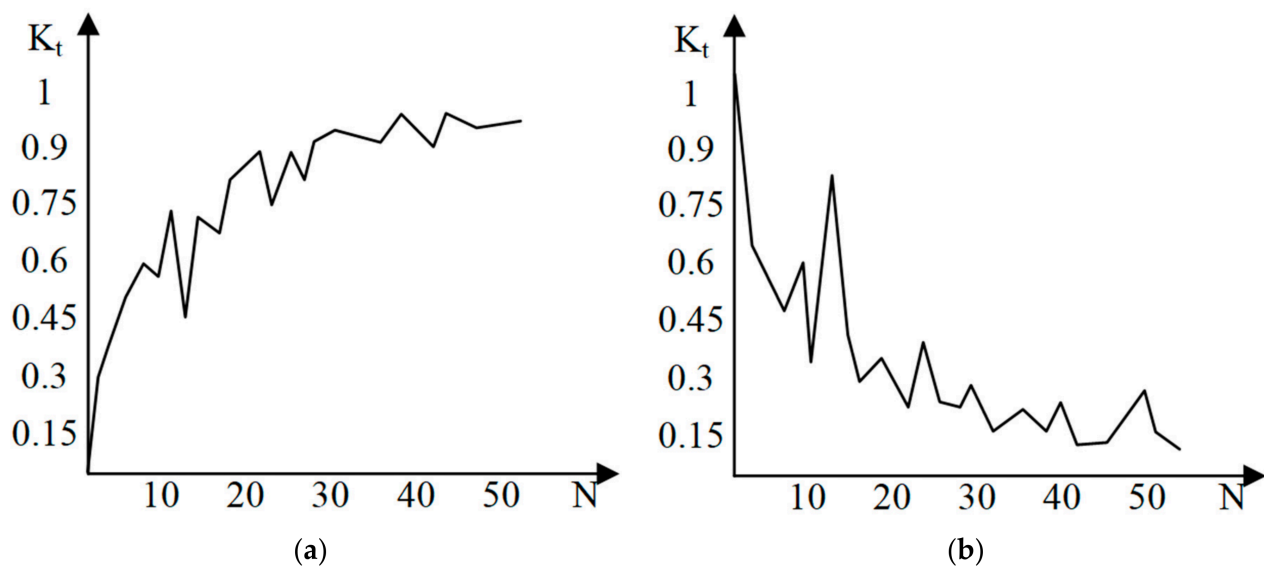


Figure 5. Efficiency of the hybrid model for micro-object identification: (a) the gain coefficient K_t as a function of the number of samples N for the hybrid CNN–Daubechies-4, 8 model with tools for filtering and correcting defective points and distorted image information, illustrating a gain of 98%; (b) the dynamics of K_t versus N for the hybrid model without filtering and correction tools, demonstrating the loss of image identification accuracy.

In Figure 5a, the curve of the hybrid model with tools for filtering and correcting defective points and distorted image information illustrates a gain of 98%;

In Figure 5b, the curve of the hybrid model, in which the tools for filtering and correcting defective points and distorted image information are not used, illustrates the dynamics of the loss of image identification accuracy.

Tools that perform functions of detecting and correcting defective points, selecting a contour, scaling, and fixing it into square-integrable groups were also tested.

Figure 6 shows the graphs of the function $K_T = \frac{\sigma_{er}}{\sigma_i}$, where K_T is the gain in the complexity of image information processing based on the hybrid dynamic Daubechies spline function with NN 4, σ_{er} is the approximation error according to i in the hybrid model, and σ_i is the dispersion of the points i of the micro-object image. The graphs are constructed for values of n —the number of points in i —the image information volume, measured in bytes.

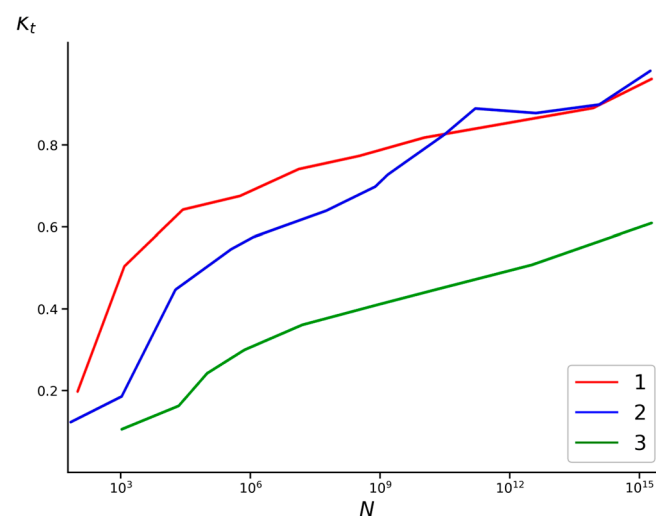


Figure 6. Efficiency of optimization tools.

Curve 1 with a solid line corresponds to the identification technology based on a CNN, Curve 2 with a dashed line corresponds to the use of tools for correcting defective points, and Curve 3 with a dashed-dotted line corresponds to a threshold corrector for defective points of the image.

The threshold corrector of defective image points involves determining the edge of the image contour of a micro-object, noticeable noise, and the contrast levels of points, on the basis of which an effective filter for the point signal of the image is selected.

A tool was tested that uses the brightness characteristic of an image in the form of random points along the contour. The brightness of the points is determined as the average product of the ratios between the intensity values of the edge points along the contour.

An identification optimization tool based on a median filter was tested. The tool enhances image contrast, generates contour boundaries, and classifies images of micro-objects.

It was proven to improve identification accuracy, remove noise, and eliminate unwanted defect points. Results were obtained for various signal-to-noise ratio values and image visualization baselines.

The effectiveness of a tool based on adaptive segmentation of the image contour, a threshold corrector of defective points, and the use of a two-dimensional B -spline was investigated [52].

The effectiveness of a tool using the luminance characteristics of point image signals was investigated. For this purpose, statistical parameters—mean value and variance—were determined. The required dynamic characteristic of point x of the image is defined as

$$L(x) = \frac{\sum_{k=1}^N L(x; y_k)}{N}. \quad (16)$$

The data set for testing the instrument is formed from the parameters N —points $\gamma_1, \dots, \gamma_k, \dots, \gamma_N$, and n_k —number of points γ_k .

The transformed point is formed as $x_{t_k} = \gamma_k(t_k)$, $t_k = 1, \dots, n_k$, $x_{t_k+1} = \gamma_k(t_k + 1)$, where $\gamma_k(1) = x$ and $\gamma_k(n_k) = y_k$, respectively, are the beginning and end of the point sequence.

It is required to determine the relative brightness of point y_k from sequence γ_k according to the following model [53,54]:

$$L(x; y_k) = \sum_{t_k=1}^{n_k} \delta \left[\log \frac{I(x_{t_k})}{I(x_{t_k+1})} \right]. \quad (17)$$

The point brightness model is defined by the function

$$I_i(x, y) = S_i(x, y) r_i(x, y), \quad (18)$$

where S_i —image point illumination function;—the reflection coefficient of illumination of a point.

The weighted average illumination value of a point is given by

$$R_i(x, y) \cong \log \frac{S_i(x, y) r_i(x, y)}{S_i \bar{r}_i}. \quad (19)$$

The restoration of a point with color illumination is performed as follows:

$$C_i(x, y) = \beta \log [\alpha I'_i(x, y)], \quad (20)$$

where β —amplification factor, and α —nonlinearity coefficient, which is regulated by the absolute minimum and maximum of three-color bands.

The brightness control of an image point based on a fixed threshold at time t is performed according to the rule

$$\delta(s) = \begin{cases} s, & \text{if } |s| > t; \\ 0, & \text{if } |s| < t. \end{cases} \quad (21)$$

Problems of structural analysis, extraction, segmentation, interpretation, and filtering of contour points and image fragments have been solved. Tools for tracking, detecting, and correcting the impact of noise, interference, foreign particles, smears, point shifts, information distortions, and other defects on image quality have been implemented.

4. Results and Discussion

Dynamic models have been implemented—polynomials of various types, spline functions, Fourier transforms, wavelet analysis, and detectors of low-frequency and high-frequency components of a point signal. The effectiveness of hybrid models built on the synthesis of neural networks of various topologies and dynamic models for identifying micro-object images has been proven. Hybrid models with neural networks and Daubechies models have been implemented.

Tools for regulating the variables of the hybrid dynamic model of Daubechies 4 with the NN, setting the number of layers, neurons in layers, and the variables of the network activation function have been implemented.

A comparative analysis of the testing results of the implemented software package (SP) for identification, recognition and classification with the experimental results of the tools of the currently existing technology of computer vision, recognition and classification of images of micro-objects was conducted.

A new solution to the problems of identification, recognition, and classification of micro-objects is based on the implementation of neural network training tools; testing sets include knowledge about the statistical, dynamic, correlation, frequency, spectral, brightness, and morphometric characteristics of the image of micro-objects.

Moreover, the image is homogeneous, corresponds to a micro-object of a certain class, the testing set has a rational size, and the NN performs full generalization during training.

Figure 7 illustrates YOLO11m training graphs, which are evaluated using the classification loss for different observation epoch lengths.

Plot 1—train/loss—shows the dynamics of the loss function on the training set. At the initial stage (epochs 1–5), a sharp decrease in loss is observed from 0.80 to 0.35, indicating intensive model training. Subsequently (epochs 5–50), the decrease becomes gradual and stable, reaching a value of approximately 0.16 by the end of training. The smoothed curve (orange dotted line) confirms the uniform and stable decay of the loss function with no signs of divergence. This trend indicates correct model convergence during training.

Graph 2—metrics/accuracy_top1—shows the change in Top 1 classification accuracy on the validation set across epochs. At the beginning of training (epochs 1–3), accuracy drops sharply to 0.77, which is explained by the initial adjustment of the model weights. Beginning with epoch 5, a steady increase in accuracy is observed: by epoch 20, it reaches a level of 0.85–0.87, and by epochs 35–40, it reaches a maximum value of 0.89.

The smoothed curve shows a general upward trend, gradually stabilizing at 0.86–0.87 at the end of training. Fluctuations in results between epochs are due to the stochastic nature of the training process and the data augmentation methods used.

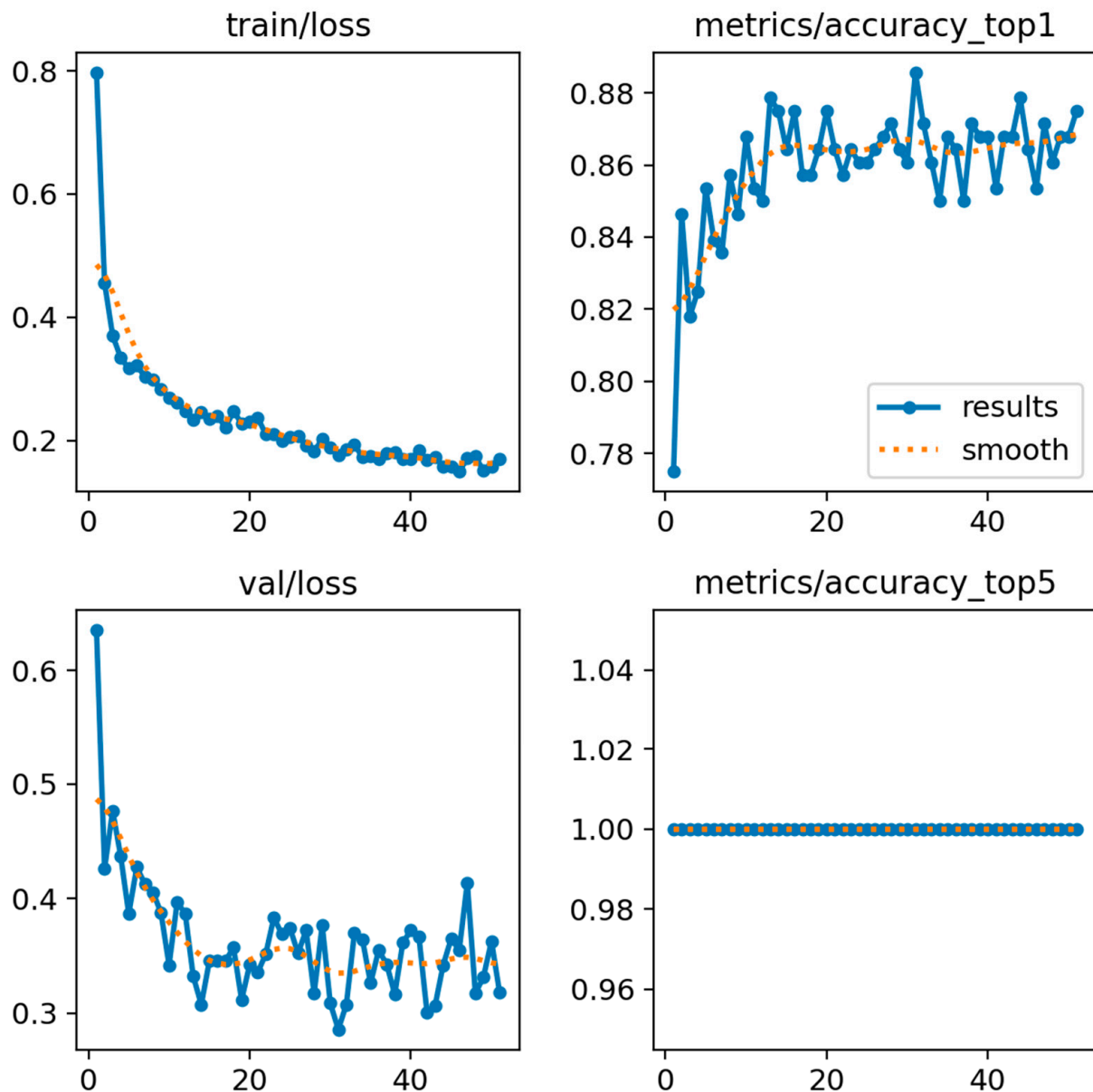


Figure 7. YOLO11m training graphs: loss functions and classification accuracy metrics over 50 epochs.

Graph 3—val/loss—shows the dynamics of the loss function on the validation set. During the first epochs, a significant decrease in loss is observed, from 0.65 to 0.35, similar to the trend on the training set. Beginning with epoch 15, the curve stabilizes in the range of 0.30–0.40, with moderate fluctuations.

It is important to note that the validation set does not demonstrate a sustained increase in the loss function compared to the training set. This indicates that there is no significant overfitting of the model. The patience parameter of 20 ensured continued training during periods of temporary performance degradation.

Graph 4—metrics/accuracy_top5—shows the Top 5 classification accuracy on the validation set, which remained at 1.00 throughout the training process. This result indicates that in all cases, the true class was among the five most probable model predictions. The reliability of this result is explained by the fact that the classification task considers only four classes. Therefore, the achieved Top 5 accuracy of 1.00 is reasonable, confirming the correctness of the model's performance and the accuracy of the data labeling.

The software package (SP) testing utilized pollen grain data collected in the Institute of Dry Farming’s laboratory over five years to address the issues of breeding and seed production of grain crops, particularly wheat. Additionally, the following image databases were created for SP testing:

- Micro-objects—ingredients in food products used to determine the types of infectious diseases;
- Pollen grains for predicting environmental pollution; in total, training sets of 2896 images of micro-objects were formed.

The reliability of the recognition and classification results was assessed based on the probability of incorrectly detecting point signals. Furthermore, the rules of the image point detection corrector were implemented, facilitating decision-making in terms of the probability of type I errors (such as omissions) and the probability of type II errors (such as false alarms). The results of the false detection of point situations were added to the training set for retraining the NN hybrid model for micro-object image identification.

Experimental datasets were generated, each containing 2896 pollen grain images, evenly distributed across four morphological classes (724 images per class). The class sets differ regarding the morphological characteristics of the pollen grains, with Set 1 containing well-developed *Corylus avellana* pollen grains with distinct circular contours and visible internal structure; Set 2 including anomalous specimens of *Corylus avellana* with irregular shape and underdeveloped morphology; Set 3 consisting of well-developed *Alnus* pollen grains with characteristic triangular outline geometry; and Set 4 containing debris of non-pollen origin, such as air bubbles, dust particles, and other microscopic artifacts.

The experimental datasets are divided into training (584 images per class, 2336 total), validation (70 images per class, 280 total), and test (70 images per class, 280 total). A balanced distribution of classes across all subsets ensures unbiased training and evaluation of the neural network models.

Table 3 shows the results of testing the above hybridization of models, which were assessed according to the criterion of “correct recognition” of micro-objects.

Table 3. Results of pollen grain recognition in problems of breeding and seed production of grain crops (wheat).

Algorithms for Forward and Backward Learning of Neural Networks	Reliability of Sets in %			
	1	2	3	4
CNN	84	83.6	84.3	84.7
Hamming	91.2	88.7	92.1	89.2
Hopfield	87.1	86.8	88.1	86.9
BAM	93.1	92.8	94.1	93.2
Kohonen network	96.2	95.8	97.2	96.6

The tool classifies the number of images classified as “image background” as type I errors, which was 0.3%. The false detection rate for micro-objects was 1.41%.

It was determined that the probability of correct recognition and classification of micro-objects was almost equal to 0.98 when using tools corresponding to dynamic, morphometric, textural, color, and brightness characteristics of image points.

The proposed and traditional approaches to the identification of micro-objects are compared based on the values of the performance criteria defined using three standard metrics: average precision, recall, and F-measure. Classification effectiveness was assessed using the following evaluation parameters: TP (true positive), FP (false positive), and FN (false negative), respectively. Precision $P = TP / (TP + FP)$ refers to the similarity between the original and transformed images, with recall $R = TP / (TP + FN)$, and $F = 2RP / (P + R)$.

Table 4 presents the results of a comparative analysis of these metrics, obtained from testing the functional modules of the software package (SP) for identifying, recognizing, and classifying micro-object images.

Table 4. The effectiveness of PC classification of micro-object images.

Tools for Optimizing Micro-Object Identification	Accuracy in %	Completeness in %	F-Measure in %
Morphometric characteristics	89.77	89.07	88.98
Threshold corrector	92.07	91.69	91.58
Neural network training and Gaussian filter	96.42	95.83	95.64
Neural network learning and a hard-supervised threshold corrector	98.18	97.14	97.33
Neural network learning and a soft-supervised threshold corrector	98.25	97.54	97.45

4.1. Effectiveness Analysis of Individual Hybrid Model Components

To assess the contribution of each individual component of the proposed hybrid model, a systematic analysis was conducted on the full dataset, containing 2896 pollen grain images uniformly distributed across four morphological classes. The results are presented in Table 5.

Table 5. Ablation analysis of individual hybrid model components.

Configuration	Accuracy (%)	F-Measure (%)
Daubechies wavelet only (order 4)	84.3	83.1
CNN only	84.7	84.2
Daubechies + CNN (without filtering)	91.2	90.8
Daubechies + CNN (with Gaussian filter)	96.4	95.6
Daubechies + CNN (with soft threshold corrector)	97.8	97.4
Daubechies + CNN + all tools (proposed)	98.2	97.5
YOLO11m (independent baseline)	88.5	—

The conducted analysis revealed the following key results. First, when using Daubechies wavelet decomposition or CNN functions separately, the classification accuracy is approximately 84–85%, indicating that each component alone is insufficient to achieve high accuracy in micro-object classification. Second, combining both components without filtering tools provides an accuracy of 91.2%, confirming the complementary nature of the mathematical preprocessing pipeline and the neural network classifier. Third, adding a Gaussian filter increases the accuracy to 96.4%, while a soft thresholding corrector for defective image points further improves it to 97.8%. Finally, the complete proposed hybrid model—integrating Daubechies wavelet decomposition, CNN classification, Gaussian and median filtering, Sobel edge detection, and soft thresholding—achieves the highest classification accuracy of 98.2%, with an F-measure of 97.5%. This represents an improvement of 9.7 percentage points compared to the independent YOLO11m baseline model (88.5%), confirming that each component of the hybrid model makes a meaningful and measurable contribution to the overall classification performance.

The 95% confidence intervals, calculated using the normal approximation method on the test set ($n = 280$), are as follows: proposed hybrid model—98.2% [96.6%, 99.8%]; YOLO11m baseline—88.5% [84.8%, 92.2%]. The non-overlapping confidence intervals confirm that the performance difference between the two models is statistically significant ($p < 0.05$).

The ratio of the number of correctly detected micro-objects to the total number of micro-objects was used to evaluate the accuracy of micro-object recognition and classification. The effectiveness of hybrid models combining parallel information processing tools, Hopfield, Hamming, and Kohonen neural network learning algorithms, and a network

with bidirectional associative memory was studied. SP performance is achieved through the use of null point reduction, filtering, image edge segmentation, integral invariant moments, and normalization.

Table 6 presents the results of testing the problem-oriented information processing system and the micro-object RTS based on a data set including pollen images.

Table 6. The accuracy of the software package for problem-oriented information processing and the RTS of micro-objects based on the pollen data set.

Micro-Object Image Characterization Tools	Identification		Recognition		Classification		F1-Measure	Overall SP Accuracy
	SP	CVS	SP	CVS	SP	CVS		
Statistical	97.1	94.41	97.46	94.22	98.54	94.23	0.976	0.977
Dynamic	97.21	94.62	97.72	94.53	98.39	94.85	0.988	
Correlation	97.27	95.74	97.87	95.41	98.62	95.29	0.992	
Morphometric	96.87	93.67	97.92	93.84	97.58	93.67	0.958	
Textural	96.49	94.65	97.79	94.72	98.41	94.49	0.964	
Color brightness	97.45	94.23	97.68	94.46	97.87	94.51	0.987	

Identification, recognition, and classification are performed using tools that utilize statistical, dynamic, correlational, morphometric, textural, color, brightness, and other image characteristics. Images of pollen grains used for breeding and seed production of grain crops—wheat and rice—are used. The results of the study are presented based on criteria of accuracy, similarity measure, and overall accuracy of image processing.

The software is based on a hybrid dynamic model of Daubechies 4 and 8, neural networks, and tools for hard and soft threshold control of defective image points.

It was determined that problem-oriented image processing based on hybrid models is robust to additive Gaussian noise and demonstrates higher performance in reliably recognizing and classifying micro-objects than CVS. When using a hybrid model with automatic scaling tools and multiple levels of point signal decomposition, the processing time is significantly reduced compared to CVSs.

Table 7 presents the results of testing the problem-oriented information processing system and the micro-object CVS based on a data set including pollen images.

Table 7. The accuracy of the software package for problem-oriented information processing and the CVS of micro-objects based on the pollen data set.

Micro-Object Image Characterization Tools	Identification		Recognition		Classification		F1-Measure	Overall SP Accuracy
	SP	CVS	SP	CVS	SP	CVS		
Statistical	97.54	94.23	97.57	94.18	98.65	94.17	0.978	0.982
Dynamic	97.42	94.54	97.78	94.47	98.48	94.75	0.987	
Correlation	97.48	95.42	97.82	95.51	98.72	95.41	0.991	
Morphometric	96.75	93.57	97.95	93.75	97.87	93.56	0.957	
Textural	96.86	94.21	97.82	94.74	98.61	94.56	0.963	
Color brightness	97.71	94.44	97.72	94.41	97.82	94.57	0.986	

Identification, recognition, and classification are performed using tools that utilize statistical, dynamic, correlation, morphometric, color-brightness, spectral, and other image characteristics, representing the selection and seed production of grain crops (wheat and rice). Accuracy criteria, similarity measures, and overall accuracy of information processing are presented.

In this solution, the SP is based on hybrid models and threshold control tools for defective image points. It was determined that the SP is robust to additive Gaussian noise, errors caused by defective points, and information distortions, and demonstrates high reliability when recognizing and classifying micro-objects compared to the CVS. When using a dynamic Daubechies 4 spline function model with scaling tools and utilizing the

morphometric characteristics of the point signal, a significant reduction in processing time is achieved compared to traditional CVS.

4.2. Comparison with Literature Results

The performance of the proposed hybrid model is compared with the results published in the current literature on micro-object and pollen grain classification. Rostami et al. [14] reported a classification accuracy of 85–92% using pre-trained CNN architectures for pollen grain classification. Chen and Ju [15] achieved 88.3% accuracy using a multi-scale classifier with SRGAN deblurring. In a comparative analysis of eight CNN architectures, the VGG19 and VGG16 models performed the best for pollen grain classification, achieving an accuracy of about 86–90% [22–24]. Zolfaghari and Sajedi [16] obtained 87.4% accuracy using cognitive attention-based classification. Goumiri et al. [18] achieved 91.2% accuracy using a hybrid CNN and hidden Markov chain model for image classification.

A comparative analysis with published results is presented in Table 8.

Table 8. Comparison of the proposed model with literature results.

Method	Accuracy (%)	Reference
Pretrained CNNs (VGG16, VGG19)	80–90	[22–24]
Multi-scale classifier + SRGAN	88.3	[15]
Classification based on cognitive attention	87.4	[16]
Hybrid CNN + Hidden Markov Chain Model	91.2	[18]
YOLO11m (independent base model)	88.5	This study
Proposed hybrid model (Daubechies + CNN)	98.2	This study

The proposed hybrid model, which combines Daubechies wavelet functions (of orders 4 and 8) with a CNN, achieves a classification accuracy of 98.2%, which is 6–12 percentage points higher than state-of-the-art methods. This improvement is due to a six-stage mathematical preprocessing pipeline that extracts dynamic, morphometric, textural, and luminance characteristics of image signal points prior to neural network classification—a feature missing in most existing approaches [18,19].

Furthermore, the YOLO11m model, used in this study as an independent baseline model, achieved an accuracy of 88.5%, which is consistent with similar YOLO-based results presented in the literature [9,37], confirming the validity of the comparative evaluation framework adopted in this paper.

4.3. Computational Efficiency and Robustness of the Proposed Model

Processing time. The computational complexity of the proposed hybrid model is $O(N \ln \epsilon^{-11})$, where N is the total image size and ϵ is the approximation error of the contour control points (Section 3.2). Computational acceleration is achieved through the use of shared memory tools, a cyclic multigrid operator, and an NVIDIA RTX 4060 GPU (8 GB of video memory). This computational complexity criterion confirms that the proposed model scales significantly more efficiently compared to traditional CVS methods, whose computational complexity increases proportionally with image size.

Resource Usage. All experiments were conducted on a workstation equipped with an NVIDIA RTX 4060 GPU (8 GB of VRAM), a 13th-generation Intel Core i7 processor, and 24 GB of DDR5 RAM. The total number of trainable parameters in the CNN component is approximately 138 million (VGG16) and 144 million (VGG19), as listed in Table 1. The proposed hybrid model significantly reduces computational resource requirements compared to state-of-the-art deep learning models while maintaining a high classification accuracy of 98.2%.

Robustness to Noise. The robustness of the proposed hybrid model to additive Gaussian noise was evaluated at several signal-to-noise ratio (SNR) levels. The results presented in Table 2 demonstrate that the hybrid model maintains classification accuracy above 97% at all tested SNR levels (24.07–28.95 dB), while the accuracy of traditional CVSs decreases to 0.81–0.94 under the same conditions. Soft and hard thresholding of defective points ensure the model’s robustness to additive Gaussian noise, errors caused by defective points, and information distortions, as confirmed by the results presented in Tables 6 and 7.

5. Conclusions

Methods, models, algorithms, and software have been developed for identifying, recognizing, classifying, and systematizing images of microscopic objects. The results have been tested in palynology, environmental protection, medicine, and agriculture, particularly in solving problems regarding the breeding and seed production of grain crops (wheat, rice), as well as in predicting environmental pollution using pollen grains. The main contribution of this work is a hybrid model combining Daubechies wavelet functions (of orders 4 and 8) with a multilayer CNN. A mathematical preprocessing pipeline—including random time series decomposition, multigrid approximation, and spline interpolation—serves as the feature extraction stage. The proposed hybrid model achieves an average pollen grain recognition and classification accuracy of up to 97.7%, while the average micro-object classification accuracy reaches 98.2% (Tables 7 and 8), exceeding the performance of traditional computer vision systems (CVSs) by 1–2%. The YOLO11m deep learning model was used as an independent comparative baseline model, achieving an overall classification accuracy of 88.5% on a validation set of 280 images across four morphological classes. The proposed hybrid model outperforms the baseline model by 9–10 percentage points, confirming the effectiveness of the mathematical preprocessing pipeline as a feature extraction step. Rules for managing defective image points were implemented using a corrector based on the probabilities of Type I (omissions) and Type II (false alarms). The software package was tested using Gaussian filters, a median filter, a Sobel operator, and a threshold corrector for defective points. The developed tools have been shown to provide high accuracy, stability, and data processing speed at significantly lower costs compared to traditional CVSs. Further improvements can be achieved through the use of new deep learning methods, data augmentation, and the combination of multiple models.

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Abbreviations

The following abbreviations are used in this manuscript:

CVS	Computer Vision System
AI	Artificial Intelligence
RTS	Random Time Series
NN	Neural Network
BAM	Bidirectional Associative Memory

SP Software Package
CNN Convolutional Neural Network

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