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MACHINE LEARNING ALGORITHMS AND CLASSIFICATION OF TEXURES

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ABSTRACT

The aim of the research is to develop algorithms for analyzing images obtained from various sources. The paper analyzes images of the ultrastructure of plant cell walls, obtained by transmission electron microscopy of plant raw materials, after various physicochemical and/or mechanochemical processing. The main focus is on the development of classification methods based on machine learning models. There were used learning traditional classifiers and learning deep convolution neural networks. The question of the applicability of methods for learning neural networks with many hidden layers, united under one term "deep learning" is investigated. The optimal parameters of the classifiers were selected automatically using the GridSearch function of the Sklearn software package. The work was carried out for the Institute of Solid State Chemistry and Mechanochemistry of the Siberian Branch of the Russian Academy of Sciences. The study was supported by a grant from the Russian Science Foundation (project No. 16-13-10200).

Keywords: *Textural Images, Texture Features, Electronic Microscopy, Deep Learning, Random Forest*

1. INTRODUCTION

Research is aimed at creating a scientific and technical groundwork in the field of image processing of texture type [1-4]. The aim of the research is to develop and search algorithms for analyzing images obtained from various sources, for example, using modern electron microscopic methods. In particular, images of the ultrastructure of plant cell walls, obtained by transmission electron microscopy of plant materials, after various physicochemical and/or mechanochemical processing are analyzed.

The work was carried out for the Institute of Solid State Chemistry and Mechanochemistry of the Siberian Branch of the Russian Academy of Sciences. The study was supported by a grant from the Russian Science Foundation (project No. 16-13-10200).

For the moment, there is a need in the world for the development of new functional, curative and prophylactic and sports food containing biopolymers hydrolysates, especially proteins and carbohydrates, in a digestible form.

The scientific problem, the solution of which is assumed in the project, is that the methods of hydrolysis, segregation and purification currently used for the processing of agricultural products do not allow us to process raw materials comprehensively, to involve hardly hydrolysable and nonreactive substances in the process, and to increase the reactions selectivity in a number of cases.

The liquid-phase chemical and biotechnological approaches aimed at intensifying liquid-phase hydrolysis have largely exhausted the resource. The increase of temperature of liquid-phase hydrolysis leads to partial decomposition of amino acids and the production of by-products (often allergens), the use of pure enzyme preparations with high hydrolase activity increases the cost of the product, additional segregation and purification steps complicate the technology and adversely affect the

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environment (organic solvents, effluents, by-products).

The proposed project aims at studying the processes occurring during solid-phase mechanical activation and the subsequent heterogeneous enzymatic hydrolysis of protein plant material. Fundamental knowledge obtained is able form the basis for new technologies for effective processing of agricultural products, the creation of safe and high quality, including special (functional) food products.

The existence of this problem can be explained by the complicacy of studying plant raw materials. It has several levels of structural organization: "plant tissues - cells - cell walls - polymer components of cell walls". By the way, quantify specific character is made by heterogeneous reactions, which are adverse for classical solution chemistry and biotechnology, and which limit the rate of the process with low reactivity of polymers in the solid phase state, contribute to certain specificity.

This brings us to the study of texture-type images. Really in the current time, these investigations are in demand by scientists from various fields – chemists, biologists, technologists, but often such images are processed manually at a qualitative (rarely semi-quantitative) level [5-6]. The transition to algorithms that allow operating with large amounts of data would allow us the listed areas of science to take a significant step forward, to improve existing and create new technological processes.

In this work, we continue the research presented in [7-10], passing to new more modern methods. The tasks of understanding an image at a high level, one way or another, are related to the classification and categorization of the entire image, its parts or each pixel. Therefore, in the development of computer vision, machine learning and its universal algorithms for classification, clustering, as well as artificial neural networks played an important role [11-19]. To obtain good results in the accuracy of object recognition, machine learning algorithms require a large amount of labeled (marked) data for training (learning).

The progress we are making today with deep learning [17] is that it allows computational models with multiple processing layers to learn representations of data with multiple levels of abstraction. Conventional machine learning methods tend to be limited in their ability to process raw data in its original form. Deep learning methods are learning methods with multiple layers of data analysis, obtained by composing simple but non-linear modules, each of which transforms data at one level into data at a higher, slightly more abstract level. By combining a sufficient number of such transformations, very sophisticated recognition methods can be "trained".

For classification tasks, higher levels of representation enhance input features that are important for discrimination and suppress irrelevant changes and noise. A key aspect of deep learning is that it learns from the raw data provided using a common known learning algorithm.

In our investigations, the learning algorithms use vectors containing sets of texture features (18 in total) or models using fragments (samples) of 64x64 pixels. In particular, microphotographs of sections of the straw cell wall are considered. Specialized software was developed that allows us to select fragments (samples) of 64x64 pixels in a photograph (Fig. 1) in order to create training samples.

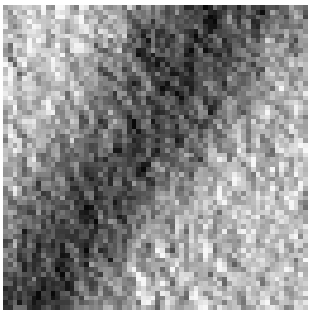

Figure 1. Example of sample

Each sample was assigned a corresponding class number. In total, 10 classes are considered, and their list is given below.

1. Gelatin.
2. Holes.
3. The grid.
4. Unformed material on the wall surface.
5. The cell wall is striped: the border between the electron-transparent layer and the layer of average electron density.
6. Cell wall: electron-transparent layers.
7. The wall is not striped.
8. Plant material that does not have an ordered (striped) structure (outside the walls).
9. Biological admixtures.
10. Resin without gelatin.

A total of 9979 samples were prepared. The diagram below shows the number of representatives of different classes (Fig. 2). Note that Type 3 samples were not prepared.

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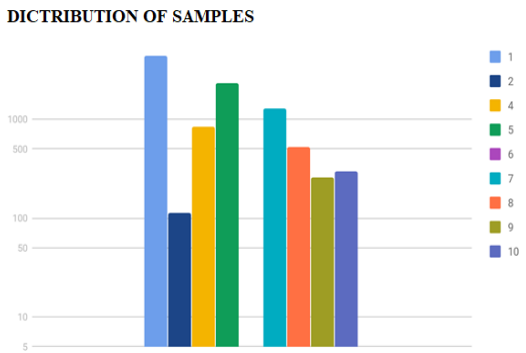

Figure 2. Distribution of samples in the training selection

It is planned that the characteristics of textural features obtained for various images (entropy, order/disorder ratio, proportion of zones with an "abnormal" texture, etc.) or fragments of images can be further correlated with values characterizing the physicochemical properties of the analyzed material: reactivity, porosity, diffusion coefficient, etc.

To carry out the correlation, also it will be possible to use machine learning algorithms, for example, based on a neurocomputer approach. So, having the learned system on a dataset, it will then be possible to make predictions regarding the physicochemical properties of materials in demand in the chemical industry. Application of machine learning methods, i.e. in fact, artificial intelligence methods in the classically applied methods of physicochemical analysis are the most interesting part of the project.

Software products that allow detailed analysis of textures can be successfully applied in various fields of science and industry. First of all, it is chemistry and materials science. You can analyze organic materials, sections of metals and minerals, ceramics, etc.

The range of tasks is not limited to the analysis of micrographs. So, when processing aerospace images, researchers also deal with different textures. It is possible to identify a coniferous or deciduous forest, fields sown with grain or legumes, etc. You can also distinguish a forest affected by pests, deserted areas.

Initially, we used classical methods for studying textures: texture features, orthogonal transformations, wavelets, R/S analysis. It was the desire of the chemists to apply machine learning methods. In our opinion, the most interesting method among them is a method based on the use of a multilevel neural network. This approach is called deep learning.

Note that the use of neural networks gives rise to many scientific problems.

1. There are problems, including in the field of image processing, which are effectively solved without using neural networks. Among these tasks is the search for objects in images. Usually, different kinds of support points are used, for example, corners. The object can be found despite the fact that it can be subjected to various transformations: parallel translation, rotation, scale changing. Affine transformations are usually not considered. Algorithms for this case also exist, but their run time is unacceptable in fields such as robotics or military applications. At the same time, in these tasks, when using the neurocomputer approach, it is necessary to "sew" too many images into the neural network. In fact, we have to repeat each image many times at different scales, at different angles, etc. And algorithm works not effectively.

2. In some cases, it is necessary to clear the initial information from various kinds of noise, discarding a large volume of data.

3. In some tasks, it is necessary to carry out special digitization of data. At the same time, a slight change in the digitizing algorithm can lead to a significant change in the operating time. This is due to the fact that the geometry of images in multidimensional space can change. In some cases simple geometry is obtained, in others it is complex.

4. Finally, some neural network algorithms are unstable. Adding minuscule noise to the original data leads to incorrect results.

If we consider images of a texture type, then machine learning algorithms, including those using the neurocomputer approach, are applicable for their study and can be recommended to other users.

The novelty of the work lies primarily in the fact that machine learning methods are applied to the study of the original (unusual) set of images. Namely, we consider micrographs obtained by transmission electron microscopy of plant raw materials ground in special mills and additionally processed by various mechanochemical methods: pulse heating to high temperatures, freezing to cryogenic temperatures, etc. The authors are not aware of similar scientific works. The second circumstance is that a rather large image classes and a large set of texture features are considered. Finally third, several methods were applied and compared.

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2. MODFELS BASED ON TRADITIONAL CLASSIFIERS

Basic difference of ideas of our project from existing analogues consists in the correct application of mathematical methods and in their deeper study. For example, it is known more than two hundred textural features. In scientific reviews, usually about fifty are mentioned. During too time, in practice, as a rule, 3-4 features are used, for example, at processing of space photos. That is they remain not investigated to the full.

The same it is possible to tell about application of integral transformations. For example, at research of durability of metals under loadings Haar transformation is used to characterize cracks. The question, what information can be received on the basis of other transformations almost is not studied. In the literature in wood chemistry it is spoken about utility of the R/S-analysis and fractal analysis for corresponding researches, but data have a sketchy character.

In our project, it is offered to approach in a complex to the given questions, i.e. to consider a big number of features, big number of transformations and create algorithms and programs, applicable for the decision of a wide class of problems.

In particular based on the available samples, several traditional classifiers [11-19] were trained: Random forest classifier, Gradient boosting, KNN (K nearest neighbors method), Deep learning (based on a multilayer [20-29] convolution neural network).

Random forest is a machine learning algorithm based on the use of an ensemble of decision trees. The algorithm is used for classification, regression and clustering problems. The main idea is to use a large ensemble of decision trees, each of which by itself gives a very low quality of classification, but due to their large number, the result is good.

Gradient boosting. Most boosting algorithms consist of iterative learning of weak classifiers in order to assemble them into a strong classifier. When they are added, some weights are usually to them given that are usually related to learning accuracy. After the weak classifier is added, the weights are recalculated, which is known as "recalculation of weights". Incorrectly classified input gains more weight, and correctly classified instances lose weight. Thus, subsequent learning focuses more on examples where the previous weak learning gave a misclassification.

KNN (K Nearest Neighbor Method) is the algorithm for automatic feature classification or regression. In the case of using the method for classification, the object is assigned to the class that is most common among the neighbors of this element, whose classes are already known. In the case of using the method for regression, the object is assigned the average value over the objects closest to it, the values of which are already known. The algorithm can be applied to samples with a large number of attributes (multidimensional). To do this, before using it, you need to set the distance function. The classic version of such function is the Euclidean metric.

Deep learning (deep learning based on a multilayer convolutional neural network) is characterized as a class of machine learning algorithms that is based on the use of neural networks.

The algorithm uses a multilayer nonlinear filter system for feature extraction. Each subsequent layer receives the output of the previous layer as input. That is, the features are organized hierarchically; the characteristics of a higher level are derived from characteristics of a lower level. Layers correspond to different levels of abstraction, in other words, layers form a hierarchy of concepts. A deep learning system can combine supervised and unsupervised learning algorithms. Sample analysis can be interpreted as unsupervised learning and classification as supervised learning.

The first option we considered. The element of the training sample is a vector, each component of which is the value of the corresponding texture feature taken over the entire sample. A total, 18 features were used. Since the number of samples in some classes in the samples is insignificant, and the entire selection is not correctly formed (balanced) in terms of quantity, it was decided not to consider small classes and among the remaining classes to choose an equal number of samples in each. Thus, only classes remained in the training sample: 1, 4, 5, 7, 8, 9, 10.

The number of samples in each class was taken equal to 520. Each sample was divided into training – 80% and test – 20%. The optimal parameters of the classifiers were selected automatically using the GridSearch function of the Sklearn software package. At the same time, the algorithms showed the following accuracy in determining the classes.

Random forest – 0.76;

Gradient boosting – 0.75;

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K nearest neighbors – 0.72.

2.1. Texture Features

Below is a list of texture features that were used in the algorithms.

The standard approach for calculating texture features is as follows. It is necessary to select the so-called running (or sliding) window with an odd side: 3, 5, 7 pixels. The feature is calculated inside the running window. The size of a local fragment is important to reflect correctly the texture properties.

The value of feature is written into a new matrix of the same size as the original one. In the new matrix, the value is written to a point with coordinates equal to the coordinates of the center of the running window. The elements of the new matrix are obtained in some interval [A, B]. Further, usually this interval is linearly mapped into the interval [0, 255]. After that, it is possible to visualize the result of calculating the texture feature.

The standard approach in our case is not very informative. Therefore, it was decided to use a non-standard approach. Namely, texture features are calculated over large windows (including non-square ones), which the user can specify by selecting an area that may be of interest to him. That is, we are talking about calculating numerical characteristics related to vast areas, including various kinds of artifacts. The 18 most important texture features are considered, and all of them are implemented in the program.

2.2. Attributes Based On Statistical Characteristics

As such features, statistical characteristics of spatial distributions can be used, calculated as measures of homogeneity from a one-dimensional histogram of signal values (characteristics of the 1st order) and from two-dimensional histograms of signal values (characteristics of the 2nd order). Thus, the following statistical characteristics can be used as numerical texture estimates from a one-dimensional histogram:

the k -th moment

$$T_1^k = n^{-2}\sum_{i=1}^{n}\sum_{j=1}^{n}[f(i,j)]^k,$$

entropy

$$T_2 = -\sum_{g=0}^{N-1}F(g)\log_{10}F(g),$$

energy

$$T_3 = \sum_{g=0}^{N-1}[F(g)]^2,$$

variation

$$T_4 = -\sum_{g=0}^{N-1}(g-\mu)^2 F(g),$$

where n is a window size in pixels,
$f(i,j)$ is a pixel brightness at a point (i,j),
N is the number of image brightness gradations,
$F(g)$ is the number of pixels having a brightness g,
μ is average brightness in the window.

The analysis shows that the texture estimates given above and calculated from a one-dimensional histogram of frequencies do not take into account the mutual arrangement of neighboring pixels in the window and only allow us to estimate the group properties of the pixels that are part of a particular image. Thus, these estimates are effective only for describing textures with unexpressed spatial regularity.

2.3. Features That Take Into Account The Relative Position.

One aspect of texture is related to the spatial distribution and spatial interdependence of the brightness values of the local area of the image with increasing distance between the estimated points. In coarse-grained textures, the brightness distribution changes much more slowly than in fine-grained ones.

The statistics of spatial interdependence of the brightness values between the nearest neighboring points are used. The adjacency matrix (or co-occurrence matrix) of brightness levels is an estimate of the second-order probability density distribution obtained from the image under the assumption that the probability density depends only on the location of two pixels.

For the formation of texture features that take into account the mutual arrangement of pixels within the sliding window, an approach based on an adjacency matrix is used. Another name is a gradient distribution matrix. In what follows, we will use the name of an adjacency matrix.

Let the analyzed image be a rectangle and has N_x horizontal elements and N_y vertical elements. Further $G = \{1,2,...,N\}$ is a set of N quantized brightness values. Then the image is described by a function from the set G into the set of brightness values, that is, $f : L_x \times L_y \to G$ where

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$L_x = \{1,2,...,N_x\}$ and $L_y = \{1,2,...,N_y\}$ are the horizontal and vertical spatial regions, respectively.

For each pixel in the image, we define the concept of a neighbor. This is a pixel different from the considered one, the coordinates of which in sets L_x and L_y differs by no more than 1 from the coordinates of the considered pixel. Thus, all non-bordering pixels of the image have 8 neighbors (Fig. 3)

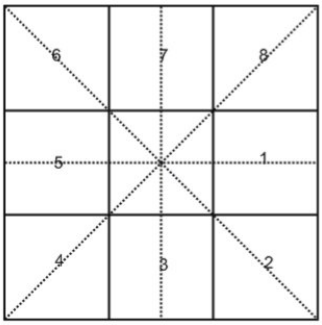

Figure 3. Adjacent pixels

Let us divide 8 adjacent pixels into 4 classes depending on how they border on the pixel in question. Neighbors numbers 1 and 5 will fall into the first class, numbers 4 and 8 in the second, numbers 3 and 7 in the third, numbers 2 and 6 in the fourth. The classes, respectively, can be called classes of directions 0, 45, 90 and 135 degrees.

The concept of a neighbor can be generalized to pixels located at a distance d from each other. We will be interested in pixels located at a distance $d = 1$ from each other and belonging to the same class of directions.

The adjacency matrix contains the relative frequencies p_{ij} of the presence in the image of neighboring elements located at a distance d from each other, with brightness $i,\ j \in G$. Usually there are horizontal ($\alpha = 0^\circ$), vertical ($\alpha = 90^\circ$) and cross-diagonal ($\alpha = 45^\circ$ and $\alpha = 135^\circ$) pairs of elements. It should be noted that these matrices are symmetric, namely $P(i,\ j,d,\alpha) = P(j,i,d,\alpha)$.

Since the number of such matrices can be very large, it is usually limited to only considering the pixels in close proximity, or the values of the elements in the matrices composed for different orientations are averaged.

Further it is shown an example (Fig. 4) of the formation of a matrix with parameters $d = 0$ and $\alpha = 0$. This is a methodological example, 8 gradations of brightness are used.

In general case, the matrix size is determined by the number of image brightness gradations. The value of each element of the matrix is equal to the number of occurrence of a pair of pixels with the corresponding values of the intensities in the given positions relative to each other.

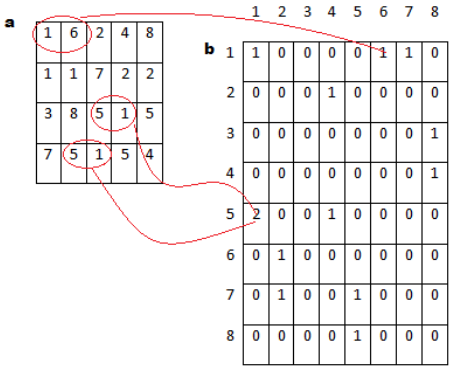

Figure 4. An example of forming an adjacency matrix

For example, the occurrence of a pair with the value (1,6) in the original image, provided that an adjacent pair is located on the same line, is equal to1, and the occurrence of a pair with a value of (5,1) is 2.

The resulting matrix is reduced to a normalized matrix:

$$p(i,\ j,d,\alpha) = \frac{P(i,\ j,d,\alpha)}{\sum_i \sum_j P(i,\ j,d,\alpha)}.$$

On the base of calculated adjacency matrices, it is possible to directly calculate the following texture features:

the average

$$T_5 = \mu_i = \mu_j = \sum_{i=0}^{N-1}\left[i \sum_{j=0}^{N-1} p(i,\ j) \right],$$

energy

$$T_6 = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} [p(i,\ j)]^2,$$

variation

$$T_7 = \sigma_i^2 = \sum_{i=0}^{N-1}\left[(i-\mu_2)^2 \sum_{j=0}^{N-1} p(i,\ j) \right],$$

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uniformity

$$T_8 = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p(i,j)/(1+|i-j|),$$

where $p(i,j)$ is the frequency of appearance of two pixels in a window with brightness i and j at an angle α at a distance *d*. Note that here new notions of energy and variation are defined.

Let σ_i be the standard deviation of the brightness in the window.

Statistical moments make possible to form texture features that take into account the relative position of neighboring pixels in the window, and accordingly, are effective for describing textures with pronounced spatial regularity.

The second angular moment

$T_9 = \sum_{i=1}^{N}\sum_{j=1}^{N}(p(i,j)/M)^2$, where M is the total number of the pairs adjoining to each other of elements (for example, for *d*=1, $\alpha = 0$, $M = 2N_y(N_x - 1)$ is a measure of uniformity (homogeneity) of the image and accepts in this case the minimum value.

Contrast $T_{10} = \sum_{n=0}^{N-1} n^2 \left[\sum_{i=1}^{N}\sum_{j=1}^{N} p(i,j)/M\right]$, $|i-j| = n$, is defined by a size of local variations of brightness of the image. With increasing the number of local variations, contrast increases.

Correlation coefficient

$$T_{11} = \sigma_x^{-1}\sigma_y^{-1} = \sum_{i=1}^{N}\sum_{j=1}^{N}[ij(p(i,j)/M) - m_x m_y],$$

where m_x, m_y, σ_x, σ_y are average values and root-mean-square deviations for $p_x(i) = \sum_{j=1}^{N} p(i,j)/M$ and $p_y(j) = \sum_{i=1}^{N} p(i,j)/M$ accordingly. T_{11} serves as a linearity measure of a regression dependence of a brightness on the image

Dispersion

$T_{12} = \sum_{i=1}^{N}\sum_{j=1}^{N}(i-m)^2(p(i,j)/M)$ defines variations of brightness concerning average value.

Reverse moment

$T_{13} = \sum_{i=1}^{N}\sum_{j=1}^{N}[1+(i-j)^2]^{-1}(p(i,j)/M)$ is closely connected with contrast and reflects a disorder degree of elements of a gradients matrix round the main diagonal. This feature is alternative to a contrast in a case of influence of regional structures, as rather big differences in values of brightness bring the minimum contribution to an end result.

Total average

$T_{14} = \sum_{n=2}^{2N} np_+(n)$, where $p_+(n) = \sum_{i=1}^{N}\sum_{j=1}^{N} p(i,j)/M$ at $i+j=n$, $n=2,\ldots,2N$ is the histogram of the sums of values of brightness. T_{14} is defined by the histogram of the sums of values of brightness $p_+(n)$ on pairs of elements of the image which is directly connected with a contiguity matrix.

Total dispersion $T_{15} = \sum_{n=2}^{2N}(n-T_{14})^2 p_+(n)$ serves as a measure of a variation of brightness concerning a total average.

Total entropy for the histogram of the sums of values of brightness $T_{16} = \sum_{n=2}^{2N} p_+(n)\log p_+(n)$ is defined by a classical measure of the statistical theory of the information and expresses the non-uniformity of a distribution brightness properties of elements of the image.

Entropy of Haralick

$T_{17} = -\sum_{i=1}^{N}\sum_{j=1}^{N}(p(i,j)/M)\log(p(i,j)/M)$ is defined the same as also total entropy, but only for a contiguity matrix.

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Difference dispersion

$$T_{18} = \sum_{n=0}^{N-1}\left[n - \sum_{m=0}^{N-1} p_{-}(m) \right]^2 p_{-}(n),$$

$|i-j|=m$ is expressed through the histogram of differences of values of brightness $p_{-}(n) = -\sum_{i=1}^{N}\sum_{j=1}^{N} P(i,j)/M$ on steams of elements of the image

Difference entropy

$T_{19} = -\sum_{n=0}^{N-1} p_{-}(n)\log p_{-}(n)$ pays off as total entropy and entropy for a contiguity matrix, but for the histogram of differences of values of brightness. Usually we do not use this characteristic, but in principal, it is interesting.

The problem of choosing informative features. It should be noted that not all considered texture characteristics are equally informative when classifying certain textures. Therefore, to increase the efficiency of algorithms, it is necessary to solve the problem of analyzing the information content and optimizing the system of features. The main issue when constructing a system of features is to determine which and how many features need to be selected for a reliable classification of objects in the image. In this case, one should be guided by the principle of taking into account the properties of the object's regularity. If the classified object has some regularity, then this regularity must be taken as the basis for the formation of a system of features. Moreover, it is necessary to ensure that this regularity is inherent in all objects belonging to a given class.

There is no formal procedure for selecting a system of features. The features used in solving certain problems are set only on the basis of the experience and intuition of a specialist. From the source system selected in this way, then in one formal way or another, a more economical and most informative subsystem of features for describing images is selected. The very process of specifying the initial system is not formalized in any way. There is an opinion that it is necessary to use everything that can only be suspected of being informative. But this is only true in principle. In practice, excessive inflation of the original system of features is not harmless. In the case of using some decision functions, adding features with a small learning sample may not only not improve, but even worsen the quality of learning.

3. CALCULATION EXAMPLES

3.1. Random forest classifier

For the Random forest method, the number of decision trees parameter was varied. The optimal number was determined to be 200. The results of applying the Random forest classifier are shown below (Fig. 5, 6). The results of other algorithms are shown next to it (Fig. 7, 8).

To mark up the image (Fig. 6–8), the same colors are used as in the diagram (Fig. 2).

The algorithms showed the accuracy of determining the classes on the validation set equal to approximately 75%.

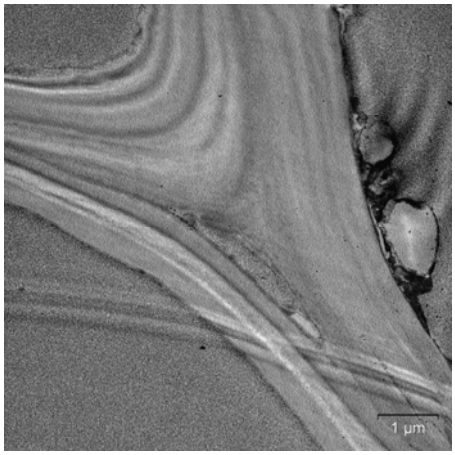

Figure 5. The initial image

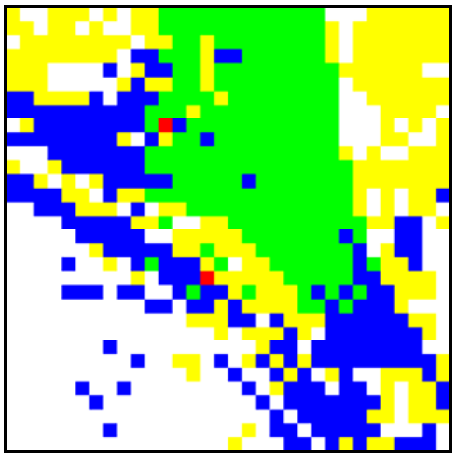

Figure 6. The result of marking a photo using the Random forest method

3.2. Gradient boosting

For gradient boosting, the parameter varied – the number of solvers.

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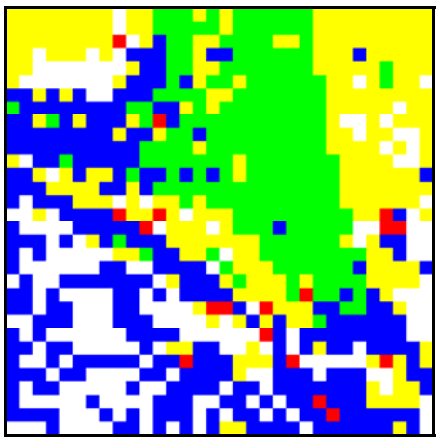

Figure 7. The result of marking the photo with the Gradient boosting classifier

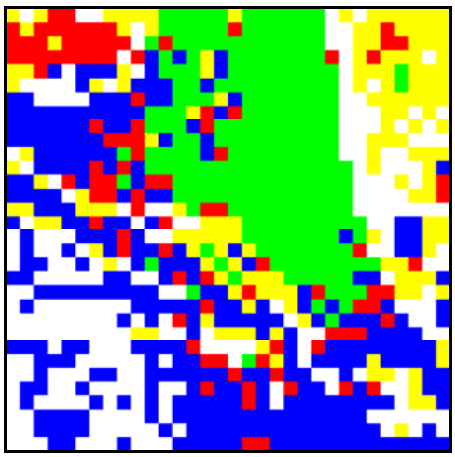

Figure 8. The result of marking the photo with the KNN classifier. The optimal number turned out to be 5.

3.3. Deep learning

A multilayer convolution neural network has been implemented. It allowed us to find the contours of the cell walls (Fig. 9).

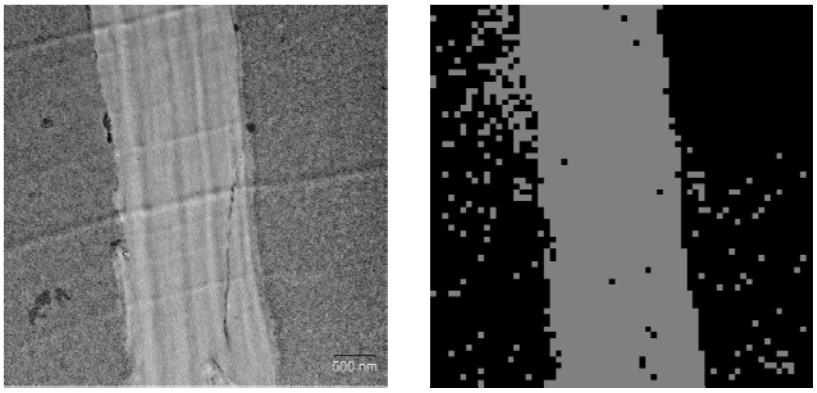

Figure 9. Results of working neural network

The architecture of the neural network is quite complex, so we will omit it from consideration. Below are examples of how the algorithm works.

4. MODEL ON THE BASE OF CONVOLUTION NEURAL NETWORK

For classification, a neural network model was used, which has 5 convolution layers. The first layer contains filters of size 4, the rest – filters of size 16. On all layers, excepting the last one, there are 20 filters with ELU activation function. The last layer has 10 layers (according to the number of classes) and Softmax activation. Each layer uses the so-called batch normalization.

Data. For training the model, data consisting of 9598 samples of 64 by 64 pixels were used, as before, 10 classes were considered.

1. Gelatin (4137 samples).
2. Holes (111 samples).
3. Grid (0 samples).
4. Unformed material on the wall surface (819 samples).
5. The cell wall is striped: the border between the electron-transparent layer and the layer of average electron density (2243 samples).
6. Cell wall: electron-transparent layers (0 samples).
7. The wall is not striped (1274 samples).

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8. Plant material without an ordered (banding) structure (outside the walls) (464 samples).
9. Biological admixtures (257 samples).
10. Resin without gelatin (293 samples).

The samples were divided into training and validation sets in a 3: 1 ratio so that the proportions within the classes were the same. The model was learned over 250 epochs with categorical cross-entropy as a loss function using the Adam optimizer with an initial learning rate of 0.0001. After each epoch, the learning rate multiplied by 0.99. The batch size was chosen equal to 64. Data augmentation was used during learning (reflections along the vertical and horizontal axes, transposition, rotations, brightness fluctuations and random Gaussian noise).

Data augmentation is an important step in training machine learning models. Data augmentation refers to increasing the data sample for training by modifying existing data.

We also used test-time augmentation – reflections and transposition. This is a way to improve the quality of the classifier through averaging. After learning, the model with the highest accuracy was selected on the validation set.

The algorithms showed the accuracy of determining the classes on the validation set equal to 79.4%. Since the model is fully convolution model, we have the ability to use it to classify each pixel in the entire image. Below is an example of the classification, and you can see the result in the following pictures (Fig. 10–12).

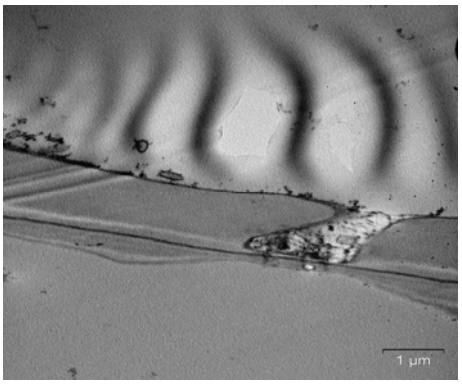

Figure 10. The initial Image

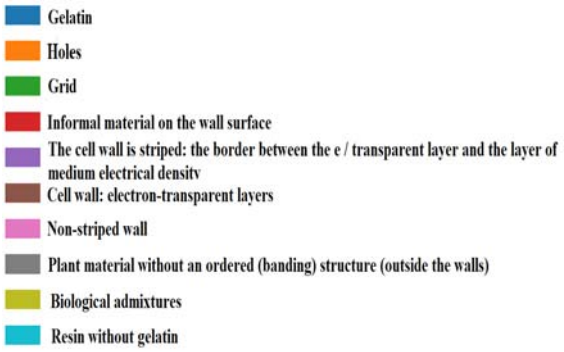

Figure 11. Color palette used to visualize result

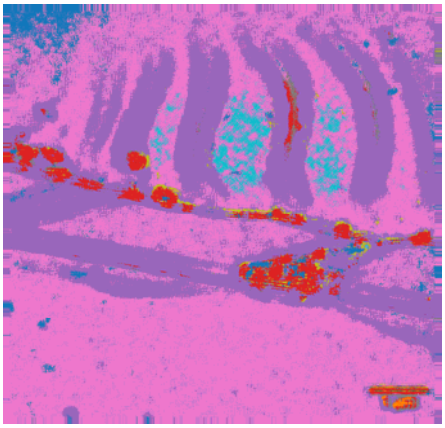

Figure 12. Results after applying neural network

5. CONCLUSION

The proposed project aims at studying the processes occurring during solid-phase mechanical activation and the subsequent heterogeneous enzymatic hydrolysis of protein plant material. The peculiarity approach is the consideration of natural polymers and plant materials – traditional objects for biotechnology – from the standpoint of solid state chemistry and materials science that to be applied [30-37].

Knowledge, experience and methods of studying heterogeneous processes occurring at the solid-liquid interphase and one often are the limiting stage are applied. The selected objects in this work is presented presented as a sophisticated and organized at the supramolecular level complex of polymers with a different chemical composition. Fundamental knowledge obtained is able form the basis for new technologies for effective processing of agricultural products, the creation of safe and high quality, including functional, food products.

The work is devoted to the study of texture images. The source is microphotographs of plant raw materials, ground by special mills. The work

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was carried out for the Institute of Solid State Chemistry and Mechanochemistry of the SB RAS.

The main result is two approaches to solving the problem of classifying and finding the contours of cell walls. Traditional classifiers and deep convolution neural networks were used, which assume a large number of training annotated data. The learning algorithms use vectors containing sets of texture features (18 in total) and models working with fragments (samples) of 64x64 pixels. During learning, data augmentation was used: reflections along the vertical and horizontal axes, transposition, rotations, brightness fluctuations and random Gaussian noise.

In this work, the following problems were solved.

1. Several traditional classifiers were learned: Random forest classifier, Gradient boosting, KNN (method of K nearest neighbors), Deep learning (based on a multilayer convolution neural network).

2. Deep convolution neural networks were learned using data, consisting of 9598 samples of 64 by 64 pixels. There were considered 10 classes.

3. Many computational experiments were carried out for the comparative analysis and evaluation of the results of the classifiers.

4. The developed methods made it possible to determine the classes with an accuracy of 79.4% and to find contours of the cell walls.

The initial hypothesis, texture-type images, that machine learning algorithms can be effectively used to classify texture-type images, including those using the neurocomputer approach, has been fully confirmed.

Algorithm which was used	Accuracy of determining the classes
Textural features method	75%
Random forest classifier	75%
Gradient boosting	73%
KNN (method of K nearest neighbors)	70%
Deep learning	79.4%

Machine learning methods were applied to the study of microphotographs obtained by transmission electron microscopy of plant materials ground in special mills and additionally processed by various mechanochemical methods. This was the main goal of the study. The authors are not aware of similar scientific works. The difference from previous works is that earlier the authors used classical methods.

The results of work can be applied in the automated systems of the analysis of images applied in scientific researches and in the industry. Application in the industry allows us to reduce the price of the analysis of the quality of the production and in some cases to raise the quality. Implementation of obtained results in systems of gathering, processing and transferring information will promote a development of a scientific and technological complex. New effective algorithms and program systems will allow us to reach technical, technological, technical and economic successes.

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