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Original Scientific Paper

Application of machine learning technology to management methods

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A b s t r a c t: Multicomponent meat system — brine injected pork and cooked sausage "Doctorskaya" were was analyzed using neural network technologies and the conditions of uncertainty and risk of human error in a decision-making process in time domain were identified. The formation of a situational classifier (digital image-based histology — meat sample sections with a detailed description) and the system's knowledge base was described. The general steps of a histological section image processing are: 1) preprocessing of section images (noise removal, palette optimization, etc.); 2) color segmentation based on palette minimization; 3) approximation of boundaries of the areas highlighted in the image; 4) area size determination; 5) particle shape determination; 6) particle color determination; 7) identification of the presence of counterfeits; 8) results' output regarding the determination of the presence of counterfeits. The Jupyter Notebook and Colaboratory software environment was used to study and compare the influence of several activation functions (ReLu, tanH, eLu, sigmoid, softPlus, softSign) on the generated DataSet. The best result was obtained when with ReLu (0.9843) activation function, followed by SoftPlus (0.9765) and eLu (0.9687) activation functions. This stage of the study considered a kind of convolutional neural network (CNN) architecture with two layers of convolution (Convolutional, C-Layer) and pooling (Subsampling, S-Layer). An algorithm of the Error Back Propagation gradient was applied to train CNN. This is the first research stage for convolutional neural network applications in solution management.

Keywords: *convolutional neural network, activation functions, intelligent system, control methods, database and knowledge, decision making.*

Introduction

The need for automation of visualization processes is out of the question. The question is how to implement artificial neural network (ANN) as effectively as possible in routine work avoiding mistakes made by the Digital Pathology Association, several years ago when using automatic diagnosing (*Van der Laak*, 2017; *Nikitina*, 2020a; *Nikitina*, 2020b). The statistical analysis of the application of this method in mammography featured many errors of the first kind (erroneous deviation from the null hypothesis).

For example, according to Korean scientists (*Kim et al.*, 2018), during medical studies, the number of errors of the first type in computer diagnostics of mammography data was about 70%. This means that when diagnosing healthy mammary glands, non-existent tumours were detected in more than half of the cases. A study (*Palazzetti et al.*, 2016) conducted by Italian scientists showed that when diagnosing malignant breast tumours such situation occurred in more than half of cases (a total of 250 cancer patients and 250 healthy women participated in the study). In the group of breast cancer patients, 138 patients (55.2%) had a truly missed cancer, 61 patients had a minimal signs and symptoms of the disease (24.4%), while a false negative result was obtained for 53 patients (20.4%). The source of errors among those who received a false negative result was in 42% of cases due to perception, in 15% — due to interpretation, 10% — due to atypical characteristics of the lesion, in 9% — due to errors during the search, in 7% — due to inherent limitations of mammography, in 4% — due to poor technique and in 13% — due to inadequate clinical management. That is, they are related to the human factor and subjectivism of perception.

The algorithm developed by specialists at the University of Nijmegen for the effective diagnosis of breast cancer based on the operation of a convo-

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lutional neural network (*Dalmış et al.*, 2018) reduces the proportion of false results.

Therefore, it is necessary to be very careful in choosing the architecture of ANN and its training. The main task is to facilitate the work of histologists and help them in making a conclusion (found/not found — compliance/non-compliance — counterfeit/not counterfeit), and not vice versa. Thus, when analyzing and classifying images, neural networks showed mediocre results, as noted above. This was observed until the development of a new architecture of ANN – convolutional neural network (CNN).

There are many methods and algorithms for solving the problem of recognizing objects in an image (*Gonzalez and Woods*, 2005; *Callan*, 1999; *Huang et al.,* 2017; *Hardt and Ma,* 2016; *Abadi et al.,* 2016), but all these ideas are not inferior in the accuracy of the result, simplicity, and speed of artificial neural networks (*Deepthi and Eswaran*, 2010). Modern deep neural networks are usually based on convolutional network-based architectures such as cognitron and neocognitron (*Yang et al.,* 2018). Their effectiveness and rapid development are due to a hybrid approach to architectural solutions, the development of learning methods, and additional error protection methods. Due to the growing popularity of deep convolutional networks, significant advances have been made in object recognition (*Lan,* 2016).

CNNs have achieved great success in image recognition, because they are arranged like the visual cortex of the brain – i.e., they can concentrate on a small area and highlight important features therein. CNN's work is usually interpreted as a transition from specific features of the image to more abstract details, and then to even more abstract details, up to the identification of high-level concepts. At the same time, the network adjusts itself and develops the necessary hierarchy of abstract features (sequences of feature maps), filtering unimportant details and highlighting essential ones. Currently, CNNs are widely used in solving medical issues.

An analysis of publications by keywords — ANN, falsification, meat products — in the ScienceDirect, Agris databases for 2014 — 2022 did showed no results. There are no studies related to artificial neural networks and meat.

An analysis of publications in the PubMed database by the keywords ANN, identification, neoplasms, showed many research related to the study of "neoplasms" in human soft tissues. In medical practice, large open databases have been collected, which are used by ANN developers. Such as: LIDC (Lung Image Database Consortium), LUNA16 (LUng Nodule Analysis 2016 Challenge), MURA (musculoskeletal radiographs), ABIDE (The Autism Brain Imaging Data Exchange), ADNI (Alzheimer's Disease Neuroimaging Initiative), DRIVE (Digital Retinal Images for Vessel Extraction), etc.

There are currently no such open or closed databases in the food industry. Therefore, the initial stage associated with the collection of input data is long and laborious. However, ideas, methods and algorithms tested in medical practice can be adapted and used in the food industry.

A few examples are given below.

Large databases have contributed to the emergence of deep learning algorithms that provide expert-level effectiveness in such tasks as the detection of diabetic retinopathy (*Gulshan et al.,* 2016), skin cancer (*Esteva et al.,* 2017), cardiac arrhythmias (*Hannun et al.*, 2019), brain hemorrhage (*Gulshan et al.*, 2016), pneumonia (*Huang et al.*, 2020) and hip fractures (*Oakden-Rayner et al.*, 2022).

In this regard, the possibility of integrating a CNN-based analysis tool to solve the problems of evaluating histological sections of food raw materials and products was of great interest.

We consider meat raw materials as muscle tissue, and the finished food product as a "biological system". That's why analogy between the identification of features on medical images and a histological images of raw meat or a finished product seems logical to us.

The study aimed at determining the main microstructural characteristics (classification parameters) for the identification of plant components in meat raw materials and finished products with CNN. By the term "finished product" we mean "ready to cook or/and ready to eat" product.

Concentration of the plant components and their nature (carrageenan, starch, soy isolate, vegetable gum) does not real matter in this case. CNN identifies them all regardless the concentrations. On the training sample, the percentage of correctly recognized samples is 97%, on the development sample — about 86%, on the test sample — 85.5%.

Materials and Methods

Samples of meat raw materials and finished meat products were used.

We use images (*.jpeg) of histological sections in RGB format to train our CNN. Histological sections were prepared according to the method from the State standard (GOST 19496-2013) "Meat and meat products. Method of histological research". The objects of the study were histological sections made from samples of: 1) cooked sausage "Doctorskaya" (recipe: pork, beef, milk, eggs, salt, black pepper) (n=50); 2) pork (m. L.dorsi) injected with brine containing plant components: soy isolate, carrageenan, gum (n=25). At least 9 sections were made from each sample. The significant minimal concentration of a plant component that can be identified with this histological method equals to 0.1%.

Histological analysis was carried out following GOST 19496-2013 "Meat and meat products. Method of histological research". The cuts 14 µm thick were prepared made using MIKROM-HM525 (Thermo Scientific) cryostat, mounted on Menzel-Glaser (Thermo Scientific) glasses, stained with Ehrlich's hematoxylin and 1% eosin water-alcohol solution (BioVitrum), and then embedded in glycerol-gelatin. Histological preparations were studied using AxioImaiger A1(Carl Zeiss, Germany) light microscope. Image processing was performed using AxioVision 4.7.1.0(Carl Zeiss, Germany) computer image analysis system and a connected AxioCam MRc 5 video camera.

To program neural networks, we used the Python language with the connection of Numpy, Keras and TensorFlow libraries (*Hoijtink and Planqué-Van Hardeveld*, 2022; *Magdin et al.,* 2022). The Numpy library helps develop a simple neural network that solves a prediction problem. The Keras library is used when programming feed-forward networks.

TensorFlow is a Google open source machine learning library used to build and train a neural network that solves the problem of finding and classifying images. The library is built on a dataflow programming paradigm that allows one to optimize mathematical calculations.

Convolutional neural network training was implemented in Jupyter Notebooks environment.

Jupyter Notebook is a tool for interactive development and presentation of software projects, a kind of notebook that combines program code in a single document.

To determine the classification accuracy, we use the activation function, which decides what should be fired into the next neuron. It takes the output signal from the previous cell and converts it into some form that can be used as input data for the next cell (Figure 1). The closer the value of the activation function to 1 (one), the more accurate recognition of the image and the assignment to the desired classification of the object.

Results and Discussion

A step-by-step solution to the problem of identifying an image of a histological cut is shown in Figure 2.

To solve this problem, it is required to collect a representative sample — DataSet with marked areas on histological cuts. Semantic segmentation is carried out in order to divide the image into separate groups of pixels that correspond to any one object (for example, carrageenan, vegetable gum, etc.).

For this purpose, a database structure has been developed, in which identification features and information about marks for testing and training are stored for each image. Before placing an image in

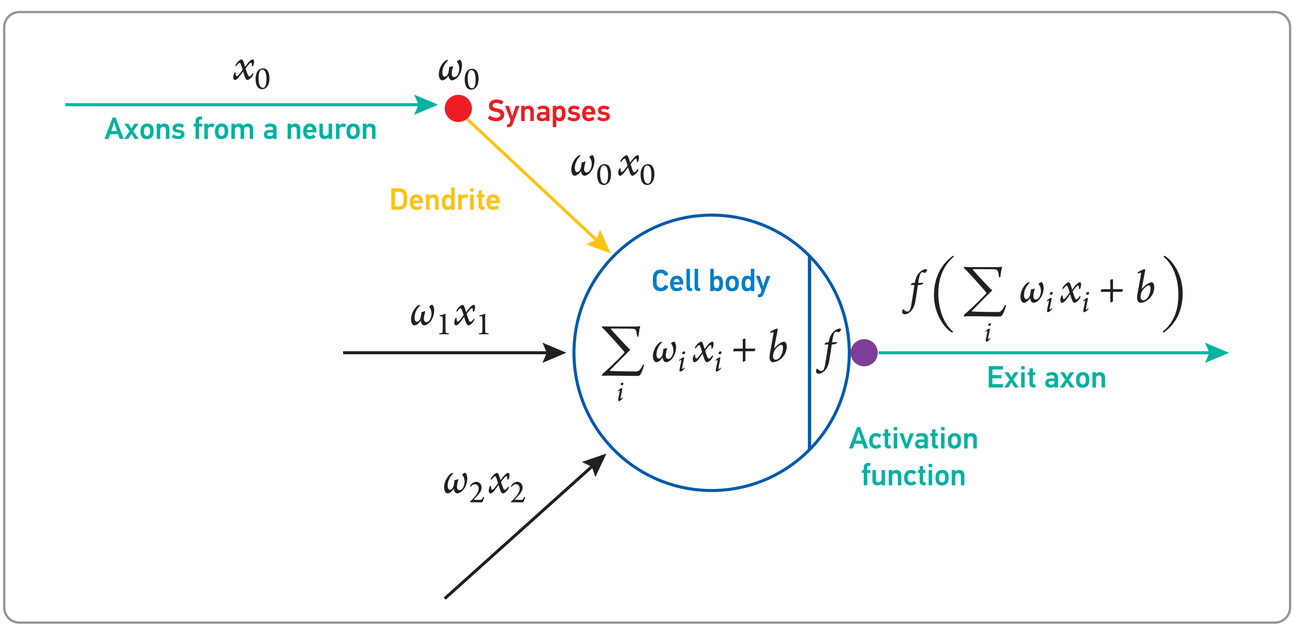


Figure 1. Artificial neuron structure

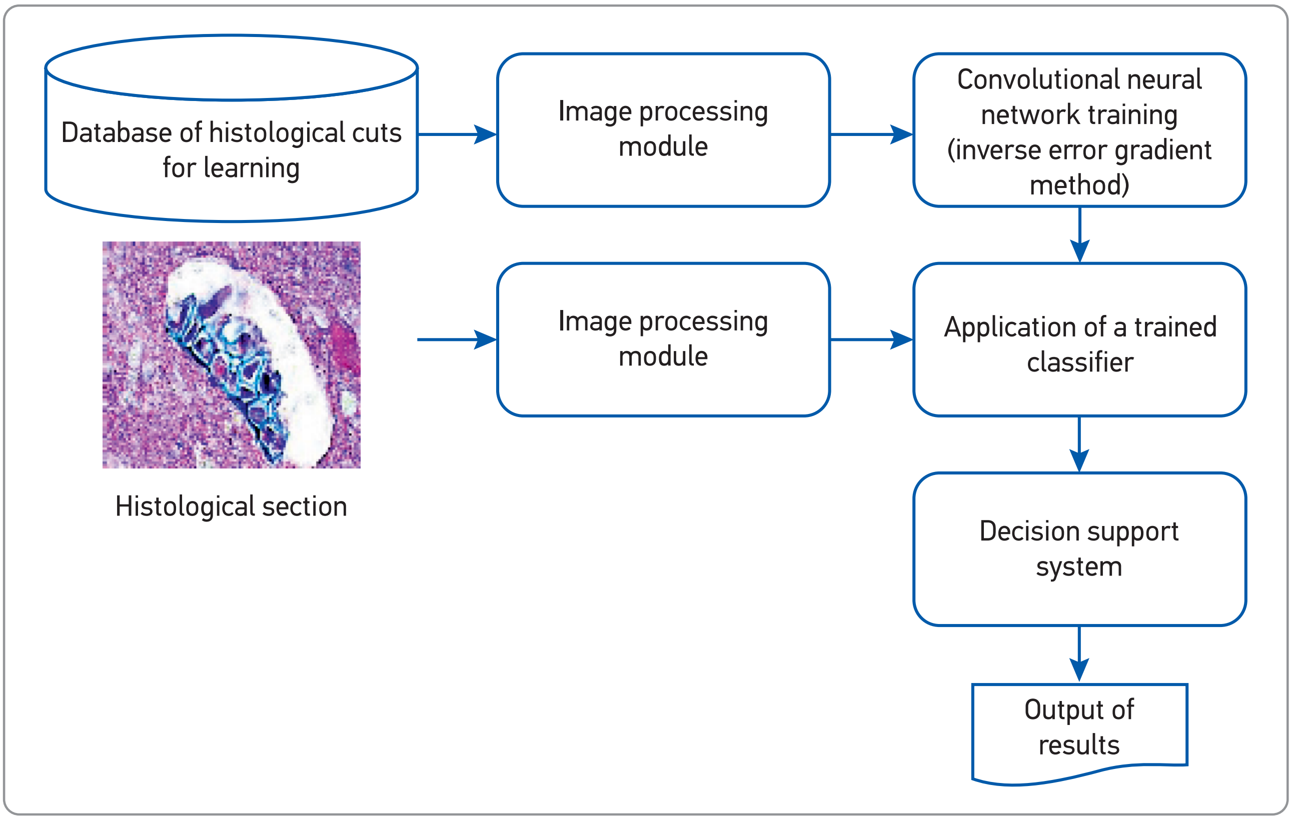


Figure 2. Step-by-step solution algorithm

the database, it undergoes pre-processing, segmentation and classification (assignment to a particular class of undeclared components).

At the training stage of the neural network, augmentation was used (changing the image, for example, flipping the image horizontally, vertically, at an angle of 45°) to increase the sample size. At least 10 variants of histological cuts were presented for each type of "inclusion". In our work, DataSet for one inclusion: the size of the training sample is 672, and the test sample is 168. The number of epoch wise trainings is 50.

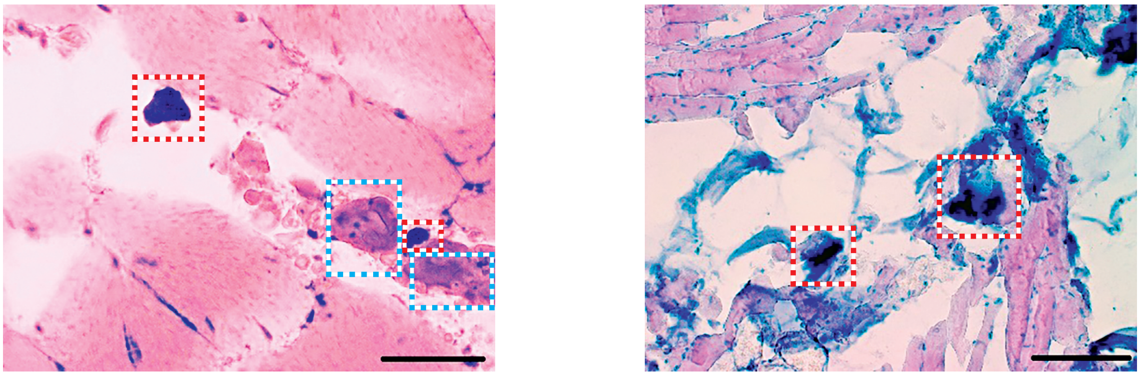
1. Database of Histological Sections

First it is necessary to collect a database of histological sections. The data must contain the same set of object classes for their segmentation. After collecting the data, it is necessary to mark up the images (Figure 3a, 3b). The marking means recording the coordinates of the polygons of each class object in a separate file in the *.txt or *.xml format.

To find the main microstructural characteristics (classification parameters/situational classifier) of identification, on the example of plant components in the composition of meat raw materials and finished products, the structure of a unified information database (DB) of histological indicators was developed in the course of the work.

The first stage included the selection of identification features that must necessarily be included in the database structure – particle shape, size, tinctorial properties of particles (the ability to be stained with histological dyes), and fragments of the soybean shell for protein components (*Lisitsyn et al.,* 2020). In this subject area, an Entity is a plant component, while an attribute is a data describing the properties/attributes of the Entity. Table 1 shows the database structure. A relational database is a (most commonly digital) database based on the relational model of data, as proposed by E. F. Codd in 1970 (*Codd,* 1970). A system used to maintain relational databases is a relational database management system (RDBMS). Many relational database systems are equipped with the option of using the SQL (Structured Query Language) for querying and maintaining the database (*Ambler,* 2009; *Khosiin and Umam*, 2023; *Hosny et al.,* 2023; *Nguyen,* 2022; *Lifschitz et al.,* 2022). Each attribute is assigned a letter designation (Table 1, Column 3).

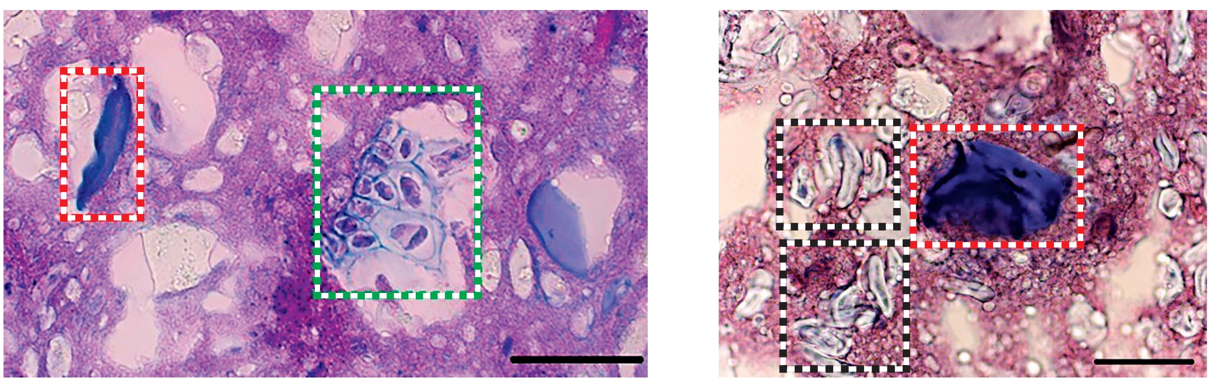
The signs specified in Column 3 corresponding to the key concepts can take certain syntactic values, which are considered as constants. If the attribute takes this value, it is assumed that the corresponding variable is equal to this value.



a) carrageenan – red;
soja isolate – blue
(Scale bar – 50 μm)

b) carrageenan – red;
(Scale bar – 200 μm)

Figure 3a. Identified plant ingredients in pork (m. L.dorsi)



a) carrageenan – red;
vegetable gum – green
(Scale bar – 50 μm)

b) carrageenan – red;
starch – black
(Scale bar – 50 μm)

Figure 3b. Identified plant ingredients in cooked sausage "Doktorskaya"

Based on the production rules, the process will be carried out as follows. An image of the histological section A is fed to the input, and then it is processed.

To implement the stages of processing images of histological sections of meat samples, the following algorithm is proposed for their implementation (Figure 4).

Processing of a histological section image A, in general, includes the following steps: 1) preprocessing of section images (noise removal, palette optimization, etc.); 2) color segmentation based on palette minimization; 3) approximation of boundaries of the areas highlighted in the image; 4) area size determination; 5) particle shape determination; 6) particle color determination; 7) identification of the pres-

Table 1. Relational Database Structure

Entity	Attribute value	Designation
Name of components	– particle shape	A_1
	– size	A_2
	– Tinctorial properties (at hematoxylin and eosin staining)	A_3
	– Tinctorial properties (at Lugol's solution staining)	A_4
	– characteristic microstructure (photo)	A_5

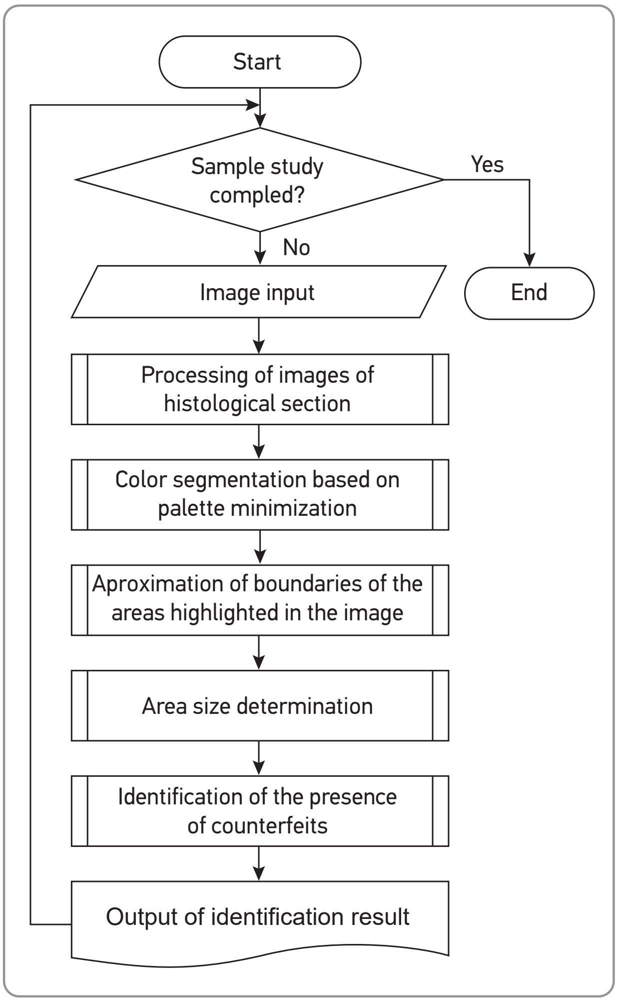


Figure 4. A block diagram of a histological section image processing algorithm to automate the detection of inconsistencies

ence of counterfeits; 8) results' output regarding the determination of the presence of counterfeits.

Consistent implementation of the above steps will allow for obtaining an informed decision on the presence or absence of certain types of counterfeits of meat products.

Based on the amount and type of a non-labeled additive (attribute *A2*), technologist, or other responsible person decides on non-compliance and further action. Like 1) return item to the supplier with complaints; 2) Send raw materials or finished product for further processing or 3) sent it to sale. This procedure is usually described in the QMS documents of an enterprise.

In neural networks, both the activation function and the error handling methods on each layer of the neural network play an important role. The accuracy of the classification made by the artificial neural network relative to the object on the histological cut depends on these two indicators. The network is considered trained when the comparison error is equal to zero or corresponds to the maximum allowable error value.

2. Activation Function

At this stage of the study, the *TensorFlow* library was used to study and compare the effect of several activation functions on classification results. The study of activation functions resulted in the obtainment of the following accuracy indicators.

We got the best result when using the ReLu activation function (0.9843). The next result was shown by the SoftPlus (0.9765), eLu (0.9687), Sigmoid (0.7851), SoftSign (0.7773), and TanH (0.7591)activation functions.

Thus, the most accurate classification is achieved by using the ReLu activation function to train a convolutional neural network (CNN) in this study.

3. Neural Network Architecture

At this stage of the study, a kind of convolutional neural network architecture with two layers of convolution (Convolutional, C-Layer) and pooling (Subsampling, S-Layer), which alternate one after another, is proposed. The CNN architecture receives a normalized image with a standardized size on the input layer, if required. Inner layers are consecutive convolution layers, with normalization and pooling layers. The main thing to understand is that a convolution layer means a layer that transforms a part of the input image, a 3×3 matrix, into a 1×1-pixel using matrix transformations. On the output layer of this type of architecture, we get a set of fitches of this image, as shown in Figure 5.

As can be seen from Figure 4, CNN consists of the following types of layers (from left to right): 1) *Convolutional* — this layer convolves the input matrix with the convolution kernel. The number of convolution kernels determines the number of feature maps — the first is equal to the second; 2) *Subsampling, or pooling layer* — this layer takes the result of the convolution of the previous layer in the form of a matrix and compresses this matrix. This is made in order to highlight low-level features and reduce the data size. The arithmetic mean of the elements over the window or the maximum value over the window is most often used as a compression function; 3) *Fully connected*. A one-dimensional vector is fed to this layer from the convolutional/subsampling layer in front of it, and this vector is obtained from the matrix by writing its elements line by line in one line.

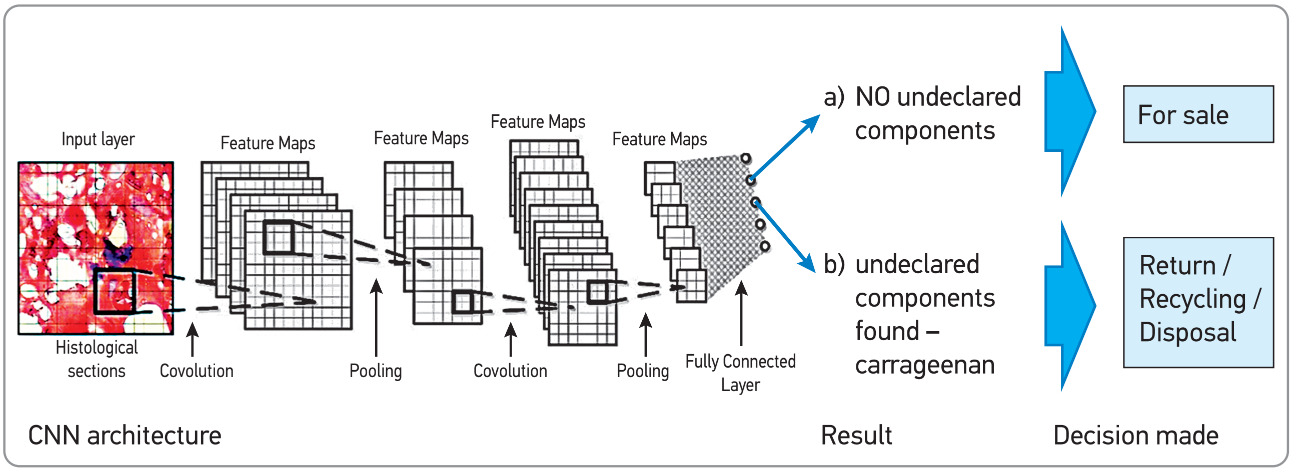


Figure 5. The CNN architecture for classification tasks of objects (undeclared components) in an image (histological section).

The main features of the CNN architecture for the classification of objects in the image are: a) the CNN *input* layer is convolutional, and the output layer is fully connected; b) *convolutional* and *sub-sample* layers alternate with each other, and their alternation is followed by fully connected layers (at least 1). Thus, the final part of CNN is nothing more than a fully connected perceptron.

An error back propagation algorithm, which refers to the methods of studying with a teacher, was used to train CNN.

Algorithm to train fully connected CNN layers. An error is formed on the last layer of CNN neurons and is defined as the difference between the output response of the network (values of neurons of the last layer of neurons) y and the standard t:

$$\gamma_j = y_j - t_j$$

Then there is a change in the values of weights and thresholds according to the formulas:

$$\omega_{ij}(t+1) = \omega_{ij}(t) - \alpha\gamma_j F'(S_j)\gamma_i$$

$$T_j(t+1) = T_j(t) + \alpha\gamma_j F'(S_j)$$

where α is the learning rate of the network; t and $t+1$ are the moments of time before and after the change of weights and thresholds, respectively; indi-

Algorithm SAG (Stochastic Average Gradient) *(Schmidt et al.,* 2017*)*

Initial data: sampling X^l, learning rate h, forgetting rate λ

Result: vector of weights w

1. Initialize weights $w_j, j = \overline{1,n}$
2. Initialize gradients $G_i = \nabla F_i(w_i), i = \overline{1,l}$
3. Initialize functionality evaluation $Q = \frac{1}{l}\sum_{i=1}^{l} F_i(w)$
4. **repeat**
5. select object x_i from X^l on a random basis
6. calculate the loss $\delta_i = F_i(w)$
7. calculate the gradient $G_i = \nabla F_i(w)$
8. make a gradient step $w = w - h\frac{1}{l}\sum_{i=1}^{l} G_i$
9. evaluate the functionality $\bar{Q} = \lambda\delta_i + (1-\lambda)\bar{Q}$
10. **until** the $\bar{Q}$ value and/or weights w converge

Figure 6. Gradient method algorithm for inverse error.

ces i and j denote the neurons of the first and second layer of neurons, respectively.

An error for the hidden layer with index i is calculated through the errors of the next layer with index j as follows:

$$\gamma_i = \Sigma_j \gamma_j F'(S_j)\omega_{ji}$$

Fully connected layers are trained according to the Rosenblatt training procedure, which presupposes that the value of the learning rate is constant during the entire training time and takes values in the interval (0;1].

Before getting to the convolutional layer or the pooling layer, the one-dimensional signal is converted into a two-dimensional one according to the same scheme.

The algorithm of the gradient method of inverse error is presented in Figure 6.

Training scheme of a convolutional neural network. First, it is necessary to initialize the weights of all layers of the neural network, set the maximum allowable error, and prepare a training set. Then the image from the first training pair is directly propagated through all layers of the neural network, while the resulting output of the neural network is compared with the required output, and the error is calculated. If the error is less than the maximum allowable value, then training stops, otherwise the error propagates backward from the last layer to the first one and the correction to the weights is calculated in each layer. After that, the weights of the neural network are modified following the gradient descent rule, while all iterations are repeated for the next training pair.

Conclusion

The state of a complex meat system in real-time under the conditions of uncertainty and risk of decision-making could be identified using neural network technologies. The paper demonstrates the formation of a situational classifier (marking of digital images of histological sections with a detailed description) and system's knowledge base. The Jupyter Notebook and Colaboratory software environment was used to study and compare the influence of several activation functions (ReLu, tanH, eLu, sigmoid, softPlus, softSign) on the generated DataSet. Classification results showed that when using the ReLu activation function, the convolutional neural network showed the most accurate classification of a given identification feature. The initial stage of solving the problems of monitoring and managing the quality of meat raw materials and finished meat products using convolutional neural networks is shown. The task of training neural networks is reduced to setting (obtaining) weight coefficients that ensure the correct operation of the neural network. Under conditions of uncertainty, evolutionary algorithms, which include genetic algorithms, show the greatest efficiency. Further research is related to the use of genetic algorithms in CNN training.

Primena tehnologije mašinskog učenja na metode upravljanja

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A p s t r a k t: Višekomponentni mesni sistem –svinjsko meso u koje je ubrizgana salamura, kao i kuvana kobasica „Doctorskaya“, analizirani su korišćenjem tehnologija neuronskih mreža i identifikovani su uslovi neizvesnosti i rizika od ljudske greške u procesu donošenja odluka u domenu vremena. Opisano je formiranje situacionog klasifikatora (histologija zasnovana na digitalnoj slici – delovi uzoraka mesa sa detaljnim opisom) i baza informacija/znanja sistema. Opšti koraci obrade slike histološkog preseka su: 1) prethodna obrada slika preseka (uklanjanje šuma, optimizacija palete, itd.); 2) segmentacija boja zasnovana na minimizaciji palete; 3) aproksimacija granica oblasti koje su istaknute na slici; 4) određivanje veličine površine; 5) određivanje oblika čestica; 6) određivanje boje čestica; 7) utvrđivanje prisustva falsifikata; 8) ishod rezultata u vezi sa utvrđivanjem prisustva falsifikata. Jupiter Notebook i Colaboratory softversko okruženje su korišćeni za proučavanje i upoređivanje uticaja nekoliko aktivacionih funkcija (ReLu, tanH, eLu, sigmoid, softPlus, softSign) na generisani skup podataka. Najbolji rezultat je postignut sa ReLu (0,9843) aktivacionim funkcijama, zatim SoftPlus (0,9765) i eLu (0,9687) aktivacionim funkcijama. U ovoj fazi istraživanja razmatrana je neka vrstu arhitekture konvolucione neuronske mreže (CNN) sa dva sloja konvolucije (Convolutional, C-Layer) i udruživanja (Subsampling, S-Layer). Za obuku CNN-a primenjen je algoritam gradijenta Error Back Propagation. Ovo je prva faza istraživanja za aplikacije konvolucionih neuronskih mreža u upravljanju rešenjima.

Ključne reči: *konvoluciona neuronska mreža, aktivacione funkcije, inteligentni sistem, metode upravljanja, baza podataka i znanja, donošenje odluka.*

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