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APPLICABILITY OF MACHINE LEARNING MODELS USING A NEURAL NETWORK FOR PREDICTING THE PARAMETERS OF THE DEVELOPMENT OF FOOD MARKETS

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Abstract: *Forecasting the parameters of the food market is a difficult task due to the volatility of demand, which depends on many factors. In this study, the authors attempted to implement a machine learning model based on multiple data on the food market. A boxed recurrent neural network was chosen as a prediction technique. The information basis was made up of data from 3,200 US cities for 2010-2012, reflecting characteristics that may be directly or indirectly related to the price of dairy products. The following models were used for data preprocessing, anomaly search, dimensionality reduction: AdaBoost, LogisticRegression, SVM. As a result of analytical actions, a neural network architecture has been formed for use in market forecasting: two competitive neural networks. First: 2 layers with Bidirectional GRU+Dropout. Second: 3 layers of LSTM+Dropout + Attention with skip-layers. Its use makes it possible to obtain a prediction model of the desired parameters with qualitative indicators of the validation sample - R^= 0.86. The applicability of the constructed machine learning model is considered on the example of classical agricultural production with the presentation of the stages of deployment of such a model at the enterprise level.*

Keywords: *machine learning, food market, neural networks, statistics, Big Data.*

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1. Introduction

The importance of understanding these issues determines the starting point of the possibility of solving them, the need for which is indicated by many policy documents adopted at the level of the international community (The Sustainable Development Goals Report, 2020; Strategic Framework 2022-2031, 2021)

Predictability is formed in the process of forecasting various economic parameters, including the potential scale of the market. In recent years, a large amount of literature has

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appeared indicating the importance of forecasting markets in solving issues of economic and political uncertainty (Carballo et al., 2022), improving the business environment, organizing more informed planning (Sazu & Jahan, 2022), production and improving inventory management (Hoffmann et al., 2022), optimization supply chains (Filali et al., 2022), development of new types of decision support systems (Zecevic et al., 2019).

In the economic literature of recent years, it is noted that many macroeconomic parameters of the market are derivatives of complex socio-economic systems that are difficult to judge within the framework of traditional linear approaches (Haynes & Alemna, 2022). Complex systems are dynamic and difficult to predict due to their high uncertainty (Bernardo & Smith, 2009; Carballo et al., 2022) and dependence on a variety of influencing and interacting factors (Castellani & Lasse, 2021).

Economic systems are certainly dynamic, which on the one hand makes it difficult to predict them, on the other hand, this dynamism, combined with the development of Internet technologies, increases the generation and availability of big data, which forms new opportunities for managing economic growth and has positive effects on it (Hodelin, 2022). The digital transformation of society is accompanied by the development of new technologies (Nikitin et al., 2020; Dubovitski et al., 2021; Karpunina et al., 2020; 2021), giving rise to new relevant research methods.

The basis for predicting the parameters of socio-economic systems is a systematic analysis of past observations, which is known as time series forecasting. One or more time series can be used for forecasting. Depending on their number, forecasting methods can be one-dimensional or multidimensional. In one-dimensional methods, the forecast is developed by constructing a working model based on the analysis of a single time series. Examples are various statistical methods, such as the analysis of averages, various one-factor regression models. In multidimensional methods, in addition to the predicted variable, forecasts are made taking into account additional time series called predictors or independent variables. These are various multifactorial correlation and regression models.

Despite the significant differences, the linear nature of the result generation is common to all these models. However, most economic processes are often nonlinear (Zhang et al., 1988), demonstrating high variability both in dynamics and in space, which reduces the quality of predictability of factors and processes.

Opportunities to avoid this contradiction are provided by the active development of machine learning methods implemented on the basis of artificial neural networks (ANN), which are able to formalize a wide range of nonlinear problems with a given level of accuracy. ANN are increasingly being used in various fields of activity (Lecun et al., 2015; Panigrahi & Behera, 2017; Demidovskij & Babkin, 2021).

There are quite a lot of ways to use machine learning models. The field of application and experimentation is mostly image processing (Jian et al., 2022). In the economic sphere, this is an analysis of financial markets and quotations of various assets (Kaminsky et al., 2020; Kerr et al., 2021). In the agricultural sector, these are the assessment of the area of contamination with weeds (Sabouri & Sajadi, 2022), assessment and mapping of the uniformity of seedlings (Vong et al., 2022), identification of varietal belonging of seeds (Ropelewska & Piecko, 2022), detection of plant diseases (Bensaadi & Louchene (2023) and many other tasks.

We find a limited number of publications on the study of forecasting issues using ANN methods (Nedeljković et al., 2019; Abbasimehr et al., 2020; Marston et al., 2021) and almost complete absence on forecasting consumption volumes, demand and prices in agri-food markets. In accordance with this, in this work, the authors have attempted to fill this gap. In this regard, the purpose of the study was to develop and test the ANN model for the purpose of forecasting the parameters of the food market.

2. Artificial neural network

The scientific foundations of modeling using neural networks were laid in the middle of the twentieth century. First, I would like to briefly define one neuron. The ancestor of the first model with one neuron is F. Rosenblatt (Rosenblatt, 1958). In 1958, while studying methods of memorizing and storing information, he managed to develop and present the first model of a single-layer perceptron designed to illustrate some fundamental properties of intelligent systems. This model was based on the fundamental concepts described in the works of N. Rashevsky (Rashevsky, 1938), W.S. McCulloch & W. Pitts (McCulloch & Pitts, 1943). Exactly F. Rosenblatt proposed the concept of a perceptron, the main idea of which was to represent the output of a neuron in the form of a linear combination of signs and weights (Fig. 1).

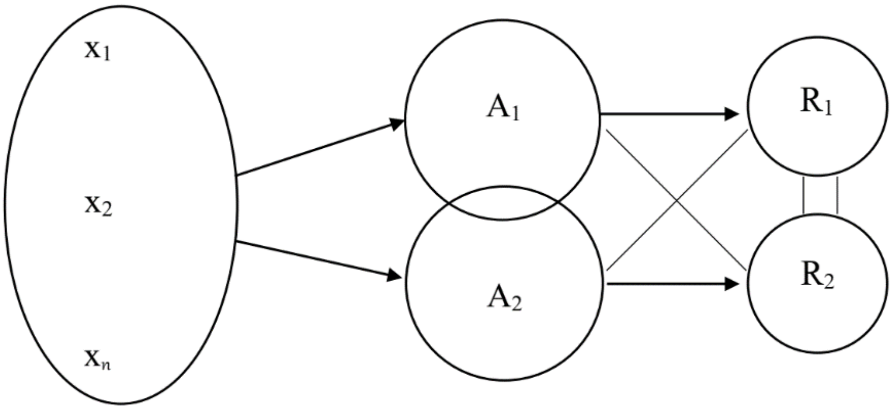

Figure 1. Single-layer perceptron
Source: Rosenblatt, 1958

Structurally, the perceptron organization is a process of calculating the algebraic sum of the initial signals (points), taking into account their significance (weight) when assessing compliance with some threshold by the system, it is enabled/disabled:

$$\text{Result} = \begin{cases} 0, \ if \ \sum_j \ w_i \, x_i \leq \theta \, (threshold) \\ 1, \ if \ \sum_j \ w_i \, x_i > \theta \, (threshold) \end{cases} \tag{1}$$

The result of the operation was a number, which was subsequently compared with a threshold value, and, depending on this, the result was determined. It is clear that such a representation of the information storage function is suitable only for solving recognition and classification problems.

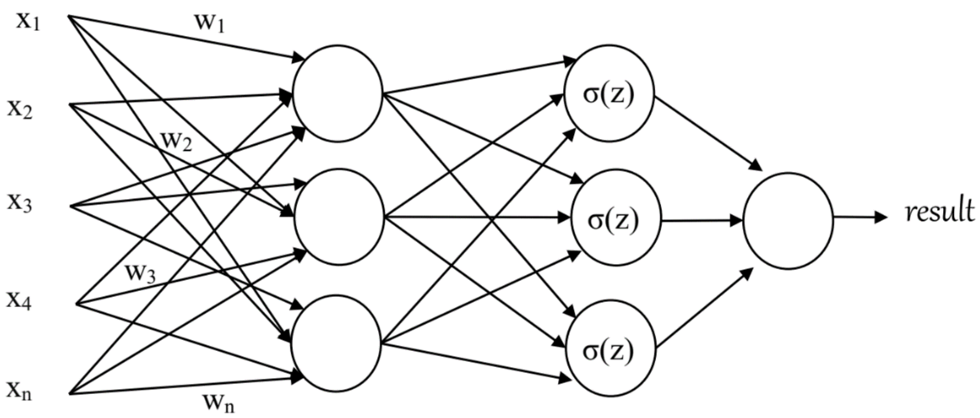

Figure 2. A single-layer neural network with a hidden layer
Source: Modified by the authors from open sources

In 1973 – 1990, it was possible to develop methods capable of just finding the weights of the model (Fig. 2). At the same time, the model was no longer a single pulse, but there was already a network of such pulses, the input of which received signs, after that, the outputs of the input layer transmitted signals to the hidden layers, those in turn aggregated the results and squeezed out the result:

$$Z = \sum_{i=1}^{N} x_i w_i + b, \tag{2}$$

x is the input vector;
w is a matrix of weights connecting the input layer and the hidden layer;
b is a free term (bias neuron), whose value is fixed and equal to 1.

The value *b* is used to increase the degree of freedom and does not depend on the input to this expression, which usually corresponds to the bias neuron (propensity).

In order to provide the possibility of training a neural network using gradient descent, a differentiable activation function is needed. The big leap was the replacement of the activation function with the so-called "sigmoid" or sigmoid function σ(z).

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{3}$$

The main advantage of this function is that it is not binary and has a non-linear nature, which allows you to build a network of several layers.

The invention of the error back propagation algorithm (Verbos, 1974; Galushkin, 1974) was of great importance for the formation of learning capabilities of multilayer perceptrons (MLP).

A great contribution to the theory of machine learning implementation was made by ElHihi and Bengio (1995), Hochreiter and Schmidhuber (1997) in the process of researching hierarchical recurrent neural networks to identify long-term dependencies, which served as the basis for many further achievements in this field.

Over the past 30 years, huge progress has been made in understanding the possibilities of modeling in various fields of knowledge, from medicine to the entertainment industry, by building artificial neural networks using various machine learning algorithms. Currently, research on improving ANN continues in the direction of increasing the scale of networks and improving performance (Dean et al., 2012), improving the architecture of networks (Huang & Chen, 2008; Bengio, 2009), minimize forecasting errors and software failures (Turabieh et al., 2019), as well as many other issues.

3. Materials and methods

The information base was open data on 3200 US cities for 2010-2012, reflecting the characteristics that may be directly or indirectly related to the food market. The milk price level was used as a predicted parameter of the consumer market.

The neural network architecture for use in market forecasting was based on the comparison and combination of two recurrente neural networks.

First: A network with long-term and short-term memory (LSTM) capable of forecasting based on processing time series with indefinite duration and boundaries (Hochreiter & Schmidhuber 1997).

Second: Bi-Directional Gated Recurrent Unit (GRU) with a back propagation algorithm used in training to predict missing points in a data set (Cho et al., 2014).

To eliminate the problem of retraining in neural networks, the Dropout algorithm was used, which allows randomly dropping units (along with their connections) from the neural network during training. This greatly simplifies the operation of the network compared to other regularization methods and increases the accuracy of forecasting (Srivastava et al., 2014).

Applied models were used for data preprocessing, anomaly search, dimensionality reduction: AdaBoost, LogisticRegression, SVM. In this article we give a concrete example of how an artificial neural network can be implemented at a specific agricultural enterprise.

4. Building a machine learning model based on ANN

Forecasting the parameters of the food market as one of the components of material flow management can provide information representing quantitative and qualitative characteristics of the processes of formation, transportation, trade and satisfaction of the needs of end consumers in certain goods both on a certain date and in the future. The main indicators characterizing the state of the food market are the needs for a particular product, the volume of supply of these goods and the price resulting from the market interaction of needs and supply.

A measure of long-term needs for a certain product can be an indicator such as actual consumption. Naturally, there are known differences between demand and consumption. The need acts as an objective necessity for various types of material goods, whereas consumption is only a statistically confirmed part of such needs, taking into account the already achieved development of production and financial security of consumers. In cases where the realization of needs does not encounter the limitations of the existing production base or, in relation to a single country, import restrictions, an identity can be put between demand and consumption for a sufficiently long period (Polyakov, 2005).

The study of long-term market parameters is possible and fully justified only in the case of a sufficiently high level of domestic production, market openness and free pricing mechanisms in the country, excluding unjustified administrative interference and political pressure from third countries. Only in this case can we expect approximate equality between the estimates of supply and demand, and the formation of an equilibrium price in the market.

Forecasting is very important for product manufacturers, intermediaries and sellers of goods when planning sales. In a developed market system, demand will act as a driver of market development, and supply will always strive to satisfy it (McConnell et al., 2009). Localized potential market scales act as the limit of possible expansion of production of a particular product, as well as predictors of export expansion.

It is quite obvious that the formation of trends in demand and prices for the most important products of the food market depends on many factors reflecting the situation of food supply and the economic situation of the country as a whole. Fluctuations in demand and prices for food products directly affect the dynamics of the development of enterprises in the relevant industries and affect food security.

In these conditions, it is becoming increasingly important to improve the accuracy of forecasting indicators of the state and development of food markets for the sustainable development of agriculture, as well as related transport, processing industries, wholesale and retail trade. Forecasting market parameters refers to predicting future sales based on past historical data. Its successful implementation plays an important role in state regulation of the market, ensuring social stability and food security. In this paper, the milk price level is taken as an example.

The use of modern machine learning tools based on competitive neural networks should contribute to solving the problems of forecasting the development of the situation in the food market, increasing the predictability of changes.

Recurrent neural networks (RNN) are a kind of ANN, where the connections between the elements form a directed sequence. This is what makes it possible to solve a wide range of tasks related to machine learning. This is one of the most advanced deep learning algorithms. Its advantage is based on the ability to save information when moving it between network layers, which is especially important for forecasting. In RNN, information goes through an internal loop. When RNN calculates the output layer, it takes into account not only the previous layer, but also the layer before it.

The most powerful RNN algorithms are LSTM and GRU. LSTM is a network that is built on the basis of LSTM modules that have the ability to store information for both short and long periods of time. This possibility is based on the absence of an activation function within its recurrent components.

The implementation of the learning function takes place through a sufficiently intelligent memory update at every moment of time. To do this, the "Gating Mechanism" is used, which remember gate, save gate and focus gate with which the network determines which elements of information should be forgotten, which ones should be added, and which ones should be focused on. The presence of a memory function and an information filtering mechanism are important advantages of LSTM, and the negative is the poorly implemented feedback principle. This disadvantage is eliminated in the process of building Bi-Directional GRU. The GRU architecture lacks an explicit memory block due to which the number of parameters is reduced. At the same time, it is quite simple and is represented by two recurrent layers unfolding in opposite directions:

Based on the data available in open sources reflecting the characteristics of the milk market in the USA, those that can be directly or indirectly related to the consumption of dairy products in each of the 3,200 urban-type settlements have been selected. 63 values are selected for each characteristic.

At the preliminary stage, data preprocessing was carried out, the search for anomalies of dimensionality reduction based on soft-ensemble by the method of stacking from the following models: AdaBoost, Logistic Regression, SVM.

These technologies allow us to reduce the dimension of the input vector to 10 features, which were considered the most clearly interpreted. They are presented in Table 1.

Table 1. Data slice used in training and validation of ANN

No	Name of the factor	Link to the factor	Units of measurement
1	Grocery stores	GROCPTH12	Per 1000 residents
2	Super malls and club stores	SUPERCPTH12	Per 1000 residents
3	Convenience stores	CONVSPTH12	Per 1000 residents
4	Fast Food Restaurants	FFRPTH12	Per 1000 residents
5	Students eligible for reduced-price lunch	PCT_REDUCED_LUNCH10	%
6	Participants of the school breakfast program	PCT_SBP14	%
7	Participants of the summer catering program	PCT_SFSP14	%
8	Farmers' Markets that Reported SNAP Adoption	FMRKT_SNAP13	Number of units
9	Farmers' Markets That Reported WIC Adoption	FMRKT_WIC13	Number of units
10	Poverty level	POVRATE10	%

Source: Compiled by the authors

The theoretical justification, analytical calculations and trial testing made it possible to form an optimal neural network architecture for predicting the potential price level. A hybrid forecasting ANN was formed using GRU and LSTM models. This combination made it possible to maximize the positive aspects and minimize the disadvantages of each of them.

The use of the Dropout algorithm, which reduces the likelihood of excessive retraining in neural networks, made it possible to increase the accuracy of forecasting, and the use of the Attention mechanism with the method of optimizing adaptive detection of domain objects, skip-layers, made it possible to increase the interpretability of the model

When building the network, the main goals were the following: satisfactory prediction accuracy, the desire to reduce the calculation time and reduce the need for memory, interpretability of the final model. The degree of achievement of the set goals became the criterion of the quality of the constructed model in the context of the experiment.

As a result, a network structure based on two RNN is obtained:

The first is Bi-directional GRU+Dropout.

The second is LSTM+Dropout + Attention with skip–layers.

The subsequent averaging of the two results was assumed through the implementation of the activation layer due to the Dense and Activation functions. The models were tuned on Bayesian GridSearch.

The emphasis was on preventing retraining, so elastic-net regularization, increased Dropout was used. The activation function for the first two models is selu, the weight initialization method is lecun_normal. The method of initializing weights is Adam.

An acceptable result of the model was obtained during the training process for 80 epochs (Fig. 3).

The results were validated using the Cross-validation method. The volume of the test sample is 30% of the total sample. The quality of the obtained model on the validation sample is R^2= 0.86. it can be interpreted as the amount of data variance, which is explained by the model (explained variation).

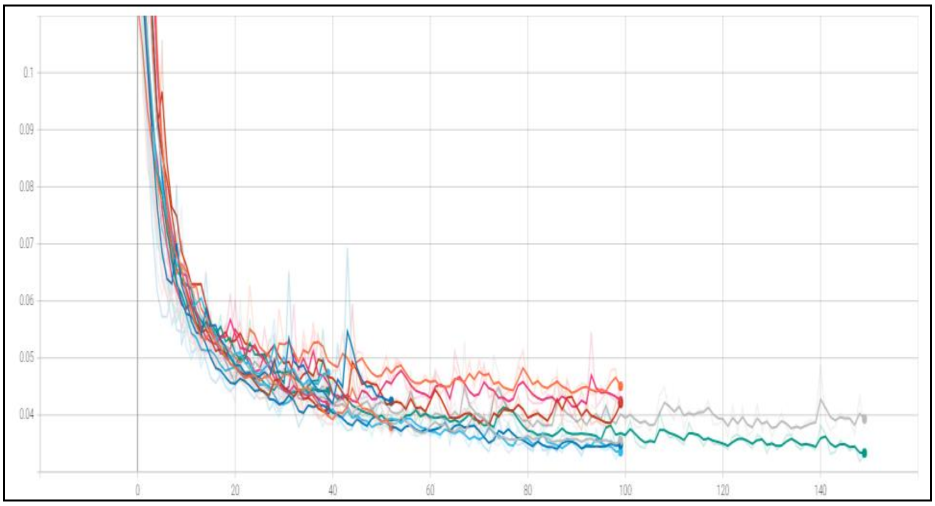

Figure 3. Log-loss graph depending on the number of epochs
Source: Authors' calculations

This result can be considered quite satisfactory, taking into account the quantity and quality of the data presented.

5. Applicability of the model at the micro level

It should be understood that after the development of the model, the result will be a poorly readable algorithm at the code level by an ordinary user. Only a well–trained specialist will be able to use such an algorithm in practice - for the most part, the one who created this algorithm. For further implementation of the algorithm in an agricultural enterprise, it is necessary to deploy an information infrastructure at the level of the enterprise itself.

We will consider the case of the introduction of a neural network into the economic department of an agricultural enterprise. Assuming that the economics department already has a standard set in the form of any client-server platform and database, we implement integration with this system to display informative graphs and diagrams. It is planned to deploy a microservice cloud infrastructure. The services will have an API in the form of gRPC using the http/2.0 protocol with a multi-multiplexing connection for accelerated data transfer. It is planned to create three microservices: for data preprocessing, for training a neural network, and for preparing data for integration and creating interactive graphs. Next, an upper-level BPMN architecture diagram will be presented (Fig. 4).

The microservice architecture of the application is the most advantageous in this case due to the ease of scaling and availability of data at any stage of information processing. The data collection and preprocessing service is responsible for data retrieval and data collection, validation and classification of data. The service must perform primary analysis of the received data, perform normalization, standardization, layout and vectorization of data for transmission to the algorithm input. The model training service is directly responsible for training the model and saving the predicted results to the database. At this stage, the neural network described above will be used. The duration of the training of the model and the results of the output directly depend on the quality, quantity and differentiation of data at the input of the model. Training of the model should be carried out regularly, but not continuously, because in this case, retraining of the model will be achieved, which in the future will have a bad effect on the results of the model. Thus, the second microservice will be launched according to the schedule formed depending on the amount of data collected by the first microservice.

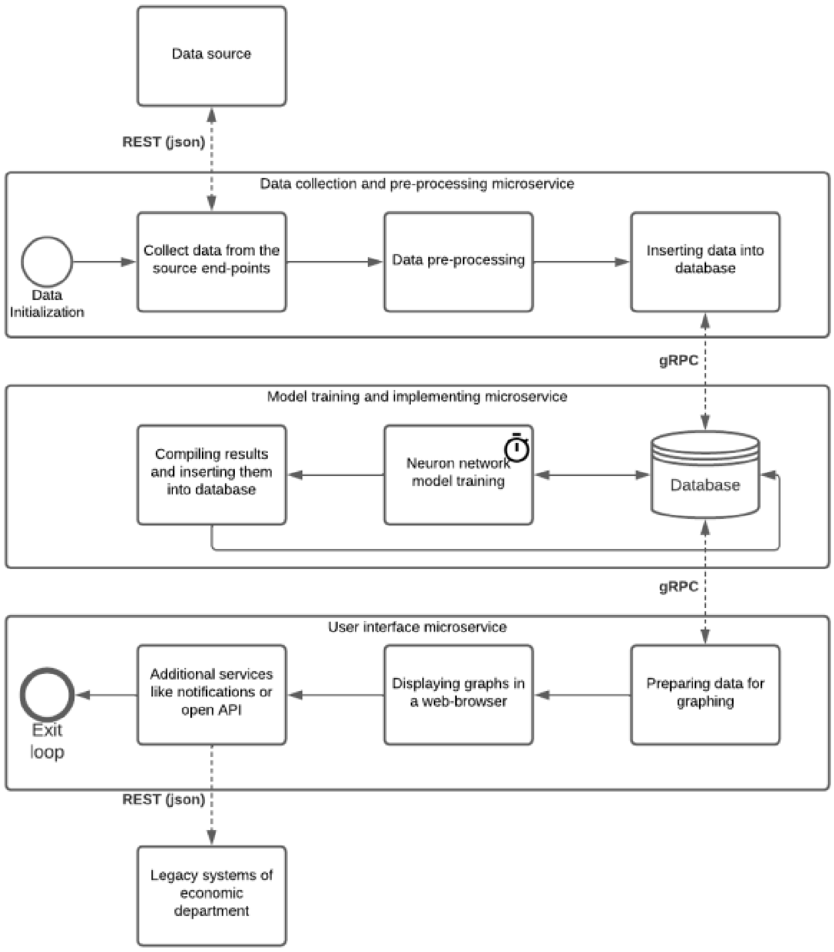

Figure 4. Top-level BPMN diagram of machine learning model deployment
Source: Compiled by the authors

The user interface microservice will be presented as a web page displaying the results of the algorithm. The most effective way to represent the predicted values in the form of a graph on top of the actual data. In this case, the predicted values are supported by actual data from the first microservice, which immediately shows the level of correlation between the predicted price and the actual price on the market. Additionally, this microservice can be used as a point of integration with other enterprise systems, as well as additional functions, such as: sending notifications to management, generating reports, logging, etc.

I would like to note that the development does not end with the creation of the model and its deployment at the enterprise. Highly loaded systems, especially those involving the use of machine learning algorithms, are unstable and prone to defects during operation. Moreover, with the advent of the system, the management will put forward new requirements for the system, which will require additional resources to refine the system and algorithms. However, the practice of large organizations associated with the analysis of the sales market shows that such systems are able to significantly increase the efficiency of product sales due to timely adjustment of product prices. Also, the data obtained as a result of collection and preprocessing can be provided on a commercial basis to other commercial and non-profit organizations.

Conclusion

In this paper, only one branch of the use of neural networks was presented. Similar models can be implemented for other parameters of the food market, and many other types of products. This requires additional efforts in this direction, and can be implemented in the future, through new research on this topic. At the same time, it should be noted that with the development of digital technologies, it is machine learning methods that are gradually becoming the basis for predicting the future state of various economic systems, including markets. In practice, the application of machine learning models is not the end point of data analysis. This is not an end in itself of analysis. In the future, the predicted data is collected in special pipelines that convert them into a format understandable to the average user. In the analysis or marketing departments, special dashboards are used that display the current situation on the market, where the results of the model are further used as additional signals for decision-making at the level of a separate department or the entire company.

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