

## Improving the efficiency of food supplies for a trading company based on an artificial neural network

Kassekeyeva Aislu Bisenovna<sup>1</sup>, Sadvakassov Arman Ashatuly<sup>1</sup>, Lamasheva Zhanar Beibutovna<sup>1</sup>, Kerimkhulle Seyit Yesilbayuly<sup>1</sup>, Abdrakhmanova Alfiya Zagievna<sup>1</sup>, Makpal Zhartybayeva Galymbekovna<sup>2</sup>, Oralkhanov Berdibek Oralkhanuly<sup>1</sup>

<sup>1</sup>Department of Information Systems, L.N. Gumilyov Eurasian National University, Astana, Kazakhstan

<sup>2</sup>Department Computer and Software Engineering, L.N. Gumilyov Eurasian National University, Astana, Kazakhstan

### Article Info

#### Article history:

Received Dec 10, 2023

Revised Mar 25, 2024

Accepted Apr 30, 2024

#### Keywords:

Artificial neural networks

Automated systems

Supply chain management

Trading network

Trading system

### ABSTRACT

This article presents the proper organization of the supply chain to meet consumer demand, which is crucial for modern commercial enterprises involved in the sale of various products. Studies indicate that a company's success is linked to the satisfaction of its customers. To optimize the supply chain, this study will consider the use of artificial neural network models. The results of this model will seek a balance between demand and supply, helping determine the necessary quantity of goods to satisfy demand and prevent overproduction. By using this model, the company can fully meet the needs of its customers. Additionally, the company saves its resources and labor costs and reallocates them to other tasks. The model demonstrates the optimization of production and supply business processes, as well as an increase in efficiency.

This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.



### Corresponding Author:

Kassekeyeva Aislu Bisenovna

Department of Information Systems, L.N. Gumilyov Eurasian National University

Astana, Kazakhstan

Email: aibike\_7474@mail.ru

## 1. INTRODUCTION

Supply chain management processes can be automated through the use of machine learning. Machine learning algorithms can be utilized to identify patterns in customer behavior, which enables businesses to adjust their supply chain strategies accordingly. By using this, businesses can better anticipate customer needs and improve their products. Automating the demand forecasting process can be achieved through machine learning, which allows businesses to better prepare to meet customer needs [1]. Machine learning algorithms enable enterprises to spot any potential violations in their processes, which allows them to take corrective measures before problems occur. Businesses can reduce costs and increase profits by increasing the speed and accuracy of supply chain processes. By doing this, they can pass on savings to their customers, leading to more competitive prices and greater customer satisfaction. The work published in other articles and national journals was studied to conduct this research. These studies were the first step towards the application of our model. One of the first was an article on the mechanism for assessing sustainable production capabilities based on blockchain technology, long short-term memory. The process of analytical hierarchy for the supply chain network was discussed [2]. In this article, the author proposed an assessment system that combines the internet of things (IoT), machine learning, and blockchain technology for the organization of the supply chain. Huang *et al.* [3] conducted research on trading systems in their work "Automated trading systems statistical and machine learning methods and hardware implementation: a survey". This paper examines trading systems constructed using various methods, dividing them into three

categories: technical analysis, text analysis, and high-frequency trading. Artificial intelligence and machine learning technologies are already being utilized by large companies to increase sales. Online stores use machine learning to recommend and select products, as well as analyze customer data such as frequency and amount of purchases, lifestyle, and favorite product categories. Self-learning algorithms are available to process large amounts of data and remember successful and unsuccessful decisions. This information is used by algorithms to make further predictions. Historical data is used to train algorithms, including transactions, customer interaction history, online sources, revenue information, and more. The model's accuracy in the end is determined by the set of data, quality, and length of the collected data. The algorithm identifies relationships and monitors the influence of various factors on the process of interest through the data array. The machine has the ability to detect even non-obvious patterns at a faster rate than a team of analysts. In addition to machine learning, there has been an increase in the research devoted to blockchain. For example, the work of Köhler and Pizzol [4] entitled "Technology assessment of blockchain-based technologies in the food supply chain". A technology assessment framework was used by the authors to examine six cases of blockchain-based technologies in the food supply chain. Technique, knowledge, organization, and product can all be distinguished by this technology. The study revealed that blockchain is not a distinct technology, but rather a component of a technology system. Blockchain technology is a database that is advanced and allows for the open exchange of information within a business network [5]. Using machine learning-based algorithms, long-term relationships with clients can be built and retention rates can be increased. Machine learning is also capable of automating customer service tasks, such as resolving simple customer queries or directing customer calls to the most suitable agent. The purpose of this study is to analyze the implementation of artificial neural networks in trading companies and their effects. In artificial intelligence, a neural network is utilized to teach computers how to process data in the same manner as the human brain. Artificial neural networks aim to achieve greater accuracy when solving complex problems, such as document summarization or face recognition [6].

## 2. METHOD

A neural network is a technique used in machine learning. The purpose of this method is to enable computers to process data in the same way as the human brain. Artificial neural networks attempt to solve complex problems in a manner similar to that of a human [7]. The study and modeling of relationships between non-linear and complex inputs and outputs is within their capabilities [8]. Neural networks have been used in a variety of industries. This can include: i) The classification of medical images for analysis; ii) Analyze behavioral data and make targeted marketing decisions through filtering and social media exploration; and iii) Making forecasts in different fields through the processing of historical data.

The structure of neural networks is a reflection of the structure of the human brain. The human brain is made up of cells called neurons that form a branched network. Each neuron in this network is connected. Sending each other special electrical signals is necessary for the human brain to process information. Artificial elements interact with each other in an artificial neural network to solve problems. Artificial neurons are what they are known as. They are software modules called nodes, and artificial neural networks are programs or algorithms that computer systems use to perform mathematical calculations [9].

Artificial neurons connect three layers in an artificial neural network [10].

- a. Input layer: The input for information from external sources is provided by the first layer. Data is processed, analyzed, or classified by nodes in this layer. Following that, it is moved to the next level.
- b. Hidden layer: The input from the input layer or other hidden layers is received by the subsequent layers. Artificial neural networks may have numerous hidden layers. The output of the previous layer is analyzed by each hidden layer, processed, and then passed on to the next layer.
- c. Output layer: The final outcome of processing all data by an artificial neural network is transmitted by this layer. There is a chance that it has one or more nodes. The output layer will have one output node that will produce a result of '1' or '0' when solving a binary classification problem (yes/no). When there are multiple classifications, the output layer may have more than one output node.

Deep neural network architecture is shown in Figure 1.

For an artificial neural network to function correctly, it must first undergo training. Special algorithms have been developed to train neural networks for these purposes. There are two main principles: supervised and unsupervised, which can be grouped and divided among all these algorithms [11]. The distinction between these two approaches lies in the fact that for certain "lessons" a teacher is necessary, while for others, independent learning is sufficient. Let's pay close attention to both methods. Finding dependencies between loosely coupled parameters can be achieved by using neural networks [12]. This is just a story about a sales forecast, where you need to take into account a huge flow of data: supplies, seasonality, weather, exchange rates, the cost of housing in the area of the outlet, the age of customers, their average

earnings, prices in similar stores, and so on. To solve such a problem, it is important to list all possible solutions in numerical format and explain how each parameter affects the others [13].

In our work, we used the backpropagation method, where the training dataset consisted of only one set of data, namely the purchase data made in the last year. Our neural network will consist of two inputs ( $a_1$  and  $a_2$ ), two hidden layers ( $b_1$  and  $b_2$ ), and two outputs ( $c_1$  and  $c_2$ ). The artificial neural network is shown in Figure 2.

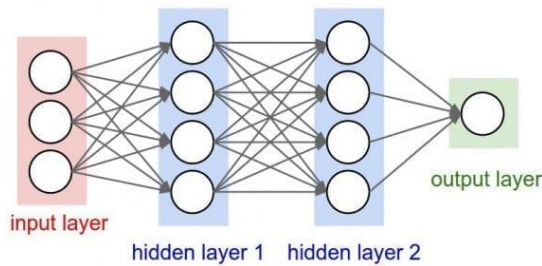


Figure 1. Deep neural network architecture

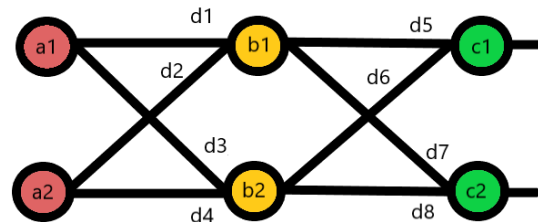


Figure 2. Artificial neural network

Using input values of 0.03 and 0.08, the neural network is obligated to produce values of 0.01 and 0.09, respectively. Our neural network will be tested against these values. The direct propagation of input signals through the layers of the neural network is the first step in the process of any neural network [14]. The initial stage involves comprehending the potential output values for input signals  $a_1=0.03$  and  $a_2=0.08$ . We take the values of the weighting coefficients as  $d_1=0.1$ ,  $d_2=0.15$ ,  $d_3=0.2$ ,  $d_4=0.25$ ,  $d_5=0.3$ ,  $d_6=0.35$ ,  $d_7=0.4$  and  $d_8=0.45$ . The input values we receive are transferred from the input layer to the hidden layer and from the hidden layer to the output layer. Calculating a weighted sum for each of the hidden layer neurons is necessary to calculate the output values of each one. The formula following allows for the calculation of the weighted sum of input signals to hidden layer neuron  $b_1$  [15]:

$$sum_{b_1} = d_1 * a_1 + d_2 * a_2$$

$$sum_{b_1} = 0.1 * 0.03 + 0.15 * 0.08 = 0.003 + 0.012 = 0.015$$

We use the activation function to calculate the output value of neuron  $b_1$  next:

$$out_{b_1} = \frac{1}{1 + e^{-sum_{b_1}}} = \frac{1}{1 + e^{-0.015}} = 0.504$$

The calculations we perform for neuron  $b_2$  are similar.

$$sum_{b_2} = d_3 * a_1 + d_4 * a_2$$

$$sum_{b_2} = 0.2 * 0.03 + 0.25 * 0.08 = 0.006 + 0.02 = 0.026$$

$$out_{b_2} = \frac{1}{1 + e^{-sum_{b_2}}} = \frac{1}{1 + e^{-0.026}} = 0.507$$

The next action is to transfer signals from the hidden layer to the output layer. The calculations are carried out in the same manner, but the outputs of the neurons in the hidden layer are used as input. Let's begin the calculations for  $c_1$  [16]–[18]:

$$sum_{c_1} = d_5 * out_{b_1} + d_6 * out_{b_2}$$

$$sum_{c_1} = 0.3 * 0.504 + 0.35 * 0.507 = 0.151 + 0.178 = 0.329$$

$$out_{c_1} = \frac{1}{1 + e^{-sum_{c_1}}} = \frac{1}{1 + e^{-0.329}} = 0.581$$

We have obtained results by performing similar calculations for neuron  $c_2$ :

$$sum_{c_2} = d_7 * out_{b_1} + d_8 * out_{b_2}$$

$$sum_{c_2} = 0.4 * 0.504 + 0.45 * 0.507 = 0.202 + 0.228 = 0.43$$

$$out_{c_2} = \frac{1}{1 + e^{-sum_{c_2}}} = \frac{1}{1 + e^{-0.43}} = 0.606$$

At the second stage, we identify a network error that has a generalized nature. To do this, we will use the formula:

$$M = \sum \frac{1}{2} (t - out)^2$$

The output expected from the neural network is ' $t$ ', while the current output is ' $out$ '. We will calculate the errors for the output neurons  $c_1$  and  $c_2$  based on this knowledge:

$$M_{c_1} = \frac{1}{2} (t_{c_1} - out_{c_1})^2 = \frac{1}{2} (0.01 - 0.581)^2 = 0.16302$$

$$M_{c_2} = \frac{1}{2} (t_{c_2} - out_{c_2})^2 = \frac{1}{2} (0.89 - 0.606)^2 = 0.04033$$

The sum of the prediction errors of all output neurons is equal to the total prediction error of a neural network.

$$M_{total} = M_{c_1} + M_{c_2} = 0.16302 + 0.04033 = 0.20335$$

The weighting coefficients can be updated using the reverse error elimination method after calculating this error. It is our duty to guarantee that the neural network produces results that are as close to the target ones as possible. New weights can be obtained and errors in the neural network can be minimized by using this method. We commence the algorithm's work from the output layer, which is the end [19].

Weights  $d_5$  and  $d_6$  have connections to neuron  $c_1$ , while weights  $d_7$  and  $d_8$  have connections to neuron  $c_2$ . We initiate the process of updating the scales using  $d_5$ . The partial derivative of  $M_{total}$  is calculated in relation to  $d_5$ . Using the rule for differentiating complex functions, we can obtain the error function if it is represented as a complex function:

$$\frac{\partial M_{total}}{\partial d_5} = \frac{\partial M_{total}}{\partial out_{c_1}} * \frac{\partial out_{c_1}}{\partial sum_{c_1}} * \frac{\partial sum_{c_1}}{\partial d_5}$$

The initial step is to determine how modifying the output signal impacts the overall network error. Because

$$M_{total} = \frac{1}{2} (t_{c_1} - out_{c_1})^2 + \frac{1}{2} (t_{c_2} - out_{c_2})^2$$

then

$$\frac{\partial M_{total}}{\partial out_{c_1}} = 2 * \frac{1}{2} (t_{c_1} - out_{c_1})^{2-1} * (-1) + 0$$

$$\frac{\partial M_{total}}{\partial out_{c_1}} = out_{c_1} - t_{c_1} = 0.581 - 0.01 = 0.571$$

Next, you need to calculate the partial derivative of its output  $out_{c_1}$  for neuron  $c_1$  with respect to the output of its adder  $sum_{c_1}$ , which forms the weighted sum of its inputs. The logistic function (sigmoid) has the peculiarity of being able to express its partial derivative in terms of itself [20].

$$\frac{\partial out_{c_1}}{\partial sum_{c_1}} = out_{c_1} (1 - out_{c_1}) = 0.581 * (1 - 0.581) = 0.2434$$

The final calculation involves determining how much the change in  $d_5$  affects the weighted sum ( $sum_{c1}$ ):

$$sum_{c1} = d_5 * out_{b1} + d_6 * out_{b2}$$

$$\frac{\partial sum_{c1}}{\partial d_5} = 1 * out_{b1} * d_5^{(1-1)} + 0 + 0 = out_{b1} = 0.504$$

After completing all the calculations, it became possible to combine them into one expression and carry out the calculation:

$$\frac{\partial M_{total}}{\partial d_5} = \frac{\partial M_{total}}{\partial out_{c1}} * \frac{\partial out_{c1}}{\partial sum_{c1}} * \frac{\partial sum_{c1}}{\partial d_5}$$

$$\frac{\partial M_{total}}{\partial d_5} = 0.571 * 0.2434 * 0.504 = 0.0701$$

Let's go back to establishing the scales, specifically the coefficient  $d_5$ . Subtracting the resulting value from the current weight is necessary to decrease the coefficient's impact on the overall network error. This value is required to be multiplied by the learning rate  $\alpha$ . Choosing the learning rate parameter is a separate task. The process of setting up neural networks has an impact on their quality and convergence. Let's assume that the value of  $\alpha$  is equal to 0.5. The  $d_5$  value will be changed to:

$$d_5^{new} = d_5 - \alpha * \frac{\partial M_{total}}{\partial d_5}$$

$$d_5^{new} = 0.3 - 0.5 * 0.0701 = 0.26495$$

To obtain corrected values for the  $d_6$  weights of the output layer, we need to perform similar operations:

$$\frac{\partial M_{total}}{\partial d_6} = 0.571 * 0.2434 * 0.507 = 0.0705$$

$$d_6^{new} = 0.35 - 0.5 * 0.0705 = 0.31475$$

The calculations for weights  $d_7$  and  $d_8$  are identical. However, there are slight differences between derivatives:

$$\frac{\partial M_{total}}{\partial d_7} = \frac{\partial M_{total}}{\partial out_{c2}} * \frac{\partial out_{c2}}{\partial sum_{c2}} * \frac{\partial sum_{c2}}{\partial d_7}$$

$$\frac{\partial M_{total}}{\partial d_7} = 0.516 * 0.2399 * 0.507 = 0.0628$$

$$d_7^{new} = 0.4 - 0.5 * 0.0628 = 0.3686$$

$$\frac{\partial M_{total}}{\partial d_8} = 0.516 * 0.2399 * 0.507 = 0.0628$$

$$d_8^{new} = 0.45 - 0.5 * 0.0628 = 0.4186$$

New weights have been identified by performing these updates in the neural network. Neurons in the hidden layer are a result of these weights. The weights that are produced are the exact weights that originally existed. It is worth remembering that the weights that were previously used were chosen at random. To update the values of weights  $d_1, d_2, d_3,$  and  $d_4$  we move from the output layer to the hidden one. Let's examine how weight  $d_1$  is updated. To start, we need to figure out how much it affects the overall network configuration error:

$$\frac{\partial M_{total}}{\partial d_1} = \frac{\partial M_{total}}{\partial out_{b1}} * \frac{\partial out_{b1}}{\partial sum_{b1}} * \frac{\partial sum_{b1}}{\partial d_1}$$

We employ an approach that is similar to the output layer. The outputs of each neuron in the hidden layer will have a simultaneous effect on multiple neurons in the output layer, which is the difference. Neuron  $b1$  has an effect on the prediction error of neurons  $c1$  and  $c2$ , which in turn has an impact on the overall network error. To assess the degree of its influence on the overall network error, it is necessary to calculate since a change in the signal  $out_{b1}$  affects both  $out_{c1}$  and  $out_{c2}$  [21].

$$\frac{\partial M_{total}}{\partial out_{b1}} = \frac{\partial M_{c1}}{\partial out_{b1}} + \frac{\partial M_{c2}}{\partial out_{b1}}$$

The first term should be written in the form

$$\frac{\partial M_{c1}}{\partial out_{b1}} = \frac{\partial M_{c1}}{\partial sum_{c1}} * \frac{\partial sum_{c1}}{\partial out_{b1}}$$

$$\frac{\partial M_{c1}}{\partial sum_{c1}} = 0.571 * 0.2434 = 0.1389$$

The second factor can be calculated in this manner

$$sum_{c1} = d_5 * out_{b1} + d_6 * out_{b2}$$

$$\frac{\partial sum_{c1}}{\partial out_{b1}} = d_5 = 0.3$$

The original expression is reconstructed by substituting the obtained values:

$$\frac{\partial M_{c1}}{\partial out_{b1}} = 0.1389 * 0.3 = 0.04167$$

Let's perform the second part of the equation in a similar manner:

$$\frac{\partial M_{c2}}{\partial out_{b2}} = \frac{\partial M_{c2}}{\partial sum_{c2}} * \frac{\partial sum_{c2}}{\partial out_{b2}}$$

$$\frac{\partial M_{c2}}{\partial out_{b2}} = 0.516 * 0.2399 * 0.45 = 0.0557$$

We can obtain that from this point onwards:

$$\frac{\partial M_{total}}{\partial out_{b1}} = 0.04167 + 0.0557 = 0.09737$$

We have identified the initial multiplier of three for  $\frac{\partial M_{total}}{\partial d_1}$ . I should mention that we are contemplating updating weight  $d_1$  and analyzing its impact on the overall network configuration error:

$$\frac{\partial M_{total}}{\partial d_1} = \frac{\partial M_{total}}{\partial out_{b1}} * \frac{\partial out_{b1}}{\partial sum_{b1}} * \frac{\partial sum_{b1}}{\partial d_1}$$

Using the formula, we calculate the second factor:

$$out_{b1} = \frac{1}{1 + e^{-sum_{b1}}}$$

This function's derivative is represented by the following form:

$$\frac{\partial out_{b1}}{\partial sum_{b1}} = out_{b1}(1 - out_{b1})$$

$$\frac{\partial out_{b1}}{\partial sum_{b1}} = 0.504 * (1 - 0.504) = 0.2499$$

The last factor will be determined using the following expression:

$$sum_{b1} = d_1 * a_1 + d_2 * a_2$$

$$\frac{\partial sum_{b1}}{\partial d_1} = a_1 = 0.01$$

The partial derivative of the total network error with respect to the weighting coefficient  $d_1$  is derived by combining all the obtained results and obtaining the final expression:

$$\frac{\partial M_{total}}{\partial d_1} = 0,09737 * 0.2499 * 0.01 = 0.00024$$

Using the same formula, we can update the values of the weighting coefficient  $d_1$  now that we are aware of the partial derivative:

$$d_1^{new} = d_1 - \alpha * \frac{\partial M_{total}}{\partial d_1}$$

$$d_1^{new} = 0.1 - 0.5 * 0.00024 = 0.09988$$

The method we use for calculating the remaining coefficients is identical:

$$\frac{\partial M_{total}}{\partial d_2} = \frac{\partial M_{total}}{\partial out_{b1}} * \frac{\partial out_{b1}}{\partial sum_{b1}} * \frac{\partial sum_{b1}}{\partial d_2}$$

$$\frac{\partial M_{total}}{\partial d_2} = 0,09737 * 0.2499 * 0.09 = 0.00218$$

$$d_2^{new} = d_2 - \alpha * \frac{\partial M_{total}}{\partial d_2}$$

$$d_2^{new} = 0.15 - 0.5 * 0.00218 = 0.14891$$

We also carry out calculations for coefficients  $d_3$  and  $d_4$ :

$$\frac{\partial M_{total}}{\partial d_3} = \frac{\partial M_{total}}{\partial out_{b2}} * \frac{\partial out_{b2}}{\partial sum_{b2}} * \frac{\partial sum_{b2}}{\partial d_3}$$

$$\frac{\partial M_{total}}{\partial d_3} = 0,09737 * 0.2499 * 0.01 = 0.00024$$

$$d_3^{new} = d_3 - \alpha * \frac{\partial M_{total}}{\partial d_3}$$

$$d_3^{new} = 0.2 - 0.5 * 0.00024 = 0.1998$$

$$\frac{\partial M_{total}}{\partial d_4} = 0,09737 * 0.2499 * 0.09 = 0.0218$$

$$d_4^{new} = d_4 - \alpha * \frac{\partial M_{total}}{\partial d_4}$$

$$d_4^{new} = 0.25 - 0.5 * 0.0218 = 0.2391$$

We successfully applied the backpropagation method. This allowed us to update the weights in our model. Comparison of weight coefficients is presented in Table 1 [22].

Table 1. Comparison of weighting factors

The meaning of the weights	Original weights	Updated weights
$d_1$	0.1	0.09988
$d_2$	0.15	0.14891
$d_3$	0.2	0.1998
$d_4$	0.25	0.2391
$d_5$	0.3	0.26495
$d_6$	0.35	0.31475
$d_7$	0.4	0.3686
$d_8$	0.45	0.4186

### 3. RESULTS AND DISCUSSION

Updated scales allow us to draw conclusions. Forward propagation resulted in a network's overall error of 0.20335. One iteration of the backpropagation algorithm led to a decrease in the network's overall prediction error to 0.19601. At first glance, this may seem like just another minor difference. However, we only used this algorithm once. The neural network's error will be significantly reduced if we perform 1,000 similar iterations. It is evident that it would be challenging for someone to carry out all these calculations on such a scale. This is where computers with their computational power come to the rescue. Virtually any programming language can implement this algorithm. This method can be used in both new and existing neural networks by implementing it programmatically [23]. In an artificial neural network aimed at improving the product supply chain, use past delivery and purchase data to train this network, and then apply this algorithm to reduce errors. As a result, the company will acquire a system that analyzes product deliveries and assists in decision-making. The potential for demand forecasting is significantly expanded thanks to neural networks. Neural networks can perform computations using a greater number of factors than human analysts. Weather, traffic congestion, competitors' marketing activities, and political events are all examples of events that can cause issues.

The use of artificial intelligence in trading is expected to expand rapidly in the future. Nowadays, there is active implementation of artificial neural networks, machine learning, and artificial intelligence everywhere. The use of neural networks is being actively initiated by enterprises. With their assistance, industrial work can be optimized, maintenance and repairs can be performed, search engine recommendations can be made, and the process and quality of work can be monitored. Processes in leading industries can be completely restructured by artificial neural networks. The main players in the market in the future will be companies that use neural networks or other types of artificial intelligence. However, neural networks possess their own unique characteristics [24]. Artificial intelligence is gradually becoming a necessity in all business sectors [25].

### 4. CONCLUSION

In conclusion, we would like to emphasize that artificial intelligence is capable of rapidly taking businesses to a whole new level. This is one of its main functions and tasks. Retail business is an example of where AI can be applied, but it can also be used in other fields. The main areas of application for artificial intelligence, artificial neural networks, and machine learning include: i) Industry (control of production processes, their optimization, equipment diagnostics, information about breakdowns, preventive measures, automation); ii) Information security (anti-fraud technologies, analysis of old threats and prevention of new ones, information for creating a common database); iii) Trade (analysis of purchasing activity and the effectiveness of marketing strategies, procurement management, development of personalized loyalty programs, in-depth analytics); iv) Trade (analysis of purchasing activity and the effectiveness of marketing strategies, procurement management, development of personalized loyalty programs, in-depth analytics); and v) Banking (risk management, forecasting, chatbots in mobile banking applications).






Companies can expand their operations and increase profits by having virtually unlimited access to new opportunities through artificial intelligence. Using just one algorithm can lead to significant performance improvements, and a comprehensive approach can yield even better results. The question is only who will be the first to implement modern technologies and achieve rapid results, and who will catch up at the very end just to stay in the market. Of course, artificial intelligence can be approached with caution and its use can be avoided, recalling the movie "Terminator". Another option is to use technology for the benefit of business, taking necessary precautions and considering the peculiarities of the models. Here, reliable, properly managed and controlled systems are important, as well as reliable partners and suppliers who can offer their expertise. Our current reality now includes artificial intelligence performing human work, and it is no longer just a fantasy. This influence will only grow stronger with each passing year due to human needs.

## REFERENCES




- [1] I. Goodfellow et al., "Deep learning," in *MIT Press*, 2016, pp. 1–800.
- [2] Z. Li, H. Guo, A. V. Barenji, W. M. Wang, Y. Guan, and G. Q. Huang, "A sustainable production capability evaluation mechanism based on blockchain, LSTM, analytic hierarchy process for supply chain network," *International Journal of Production Research*, vol. 58, no. 24, pp. 7399–7419, Mar. 2020, doi: 10.1080/00207543.2020.1740342.
- [3] B. Huang, Y. Huan, L. Da Xu, L. Zheng, and Z. Zou, "Automated trading systems statistical and machine learning methods and hardware implementation: a survey," *Enterprise Information Systems*, vol. 13, no. 1, pp. 132–144, Jul. 2018, doi: 10.1080/17517575.2018.1493145.
- [4] S. Köhler and M. Pizzol, "Technology assessment of blockchain-based technologies in the food supply chain," *Journal of Cleaner Production*, vol. 269, p. 122193, Oct. 2020, doi: 10.1016/j.jclepro.2020.122193.
- [5] D. O. Oyewola, E. G. Dada, T. O. Omotehinwa, O. Emebo, and O. O. Oluwagbemi, "Application of deep learning techniques and Bayesian optimization with tree Parzen estimator in the classification of supply chain pricing datasets of health medications," *Applied Sciences*, vol. 12, no. 19, p. 10166, Oct. 2022, doi: 10.3390/app121910166.
- [6] M. Picozzi and A. G. Iaccarino, "Forecasting the preparatory phase of induced earthquakes by recurrent neural network," *Forecasting*, vol. 3, no. 1, pp. 17–36, Jan. 2021, doi: 10.3390/forecast3010002.
- [7] M. Kouhizadeh, S. Saberi, and J. Sarkis, "Blockchain technology and the sustainable supply chain: Theoretically exploring adoption barriers," *International Journal of Production Economics*, vol. 231, p. 107831, Jan. 2021, doi: 10.1016/j.ijpe.2020.107831.
- [8] V. Sohrabpour, P. Oghazi, R. Toorajipour, and A. Nazarpour, "Export sales forecasting using artificial intelligence," *Technological Forecasting and Social Change*, vol. 163, p. 120480, Feb. 2021, doi: 10.1016/j.techfore.2020.120480.
- [9] S. Lyu and J. Liu, "Convolutional recurrent neural networks for text classification," *Journal of Database Management*, vol. 32, no. 4, pp. 65–82, Oct. 2021, doi: 10.4018/jdm.2021100105.
- [10] R. Shaikh, S. Shirazian, and G. M. Walker, "Application of artificial neural network for prediction of particle size in pharmaceutical cocrystallization using mechanochemical synthesis," *Neural Computing and Applications*, vol. 33, no. 19, pp. 12621–12640, Apr. 2021, doi: 10.1007/s00521-021-05912-z.
- [11] L. Salau, M. Hamada, R. Prasad, M. Hassan, A. Mahendran, and Y. Watanobe, "State-of-the-art survey on deep learning-based recommender systems for e-learning," *Applied Sciences*, vol. 12, no. 23, p. 11996, Nov. 2022, doi: 10.3390/app122311996.
- [12] H. Zhou, F. Xiong, and H. Chen, "A comprehensive survey of recommender systems based on deep learning," *Applied Sciences*, vol. 13, no. 20, p. 11378, Oct. 2023, doi: 10.3390/app132011378.
- [13] R. J. K. Almahmood and A. Tekerek, "Issues and solutions in deep learning-enabled recommendation systems within the E-commerce field," *Applied Sciences*, vol. 12, no. 21, p. 11256, Nov. 2022, doi: 10.3390/app122111256.
- [14] P. K. Likhari, A. Jha, S. Tiwari, A. Sunar, S. Shahu, and S. Thate, "Machine learning-based sales prediction and inventory management for grocery stores," *International Journal of Advanced Research in Science, Communication and Technology*, pp. 24–32, Nov. 2023, doi: 10.48175/ijarsct-13605.
- [15] G. Desirena, A. Diaz, J. Desirena, I. Moreno, and D. Garcia, "Maximizing customer lifetime value using stacked neural networks: an insurance industry application," *2019 18th IEEE International Conference on Machine Learning and Applications (ICMLA)*, Boca Raton, FL, USA, 2019, pp. 541–544, doi: 10.1109/icmla.2019.00101.
- [16] H. Li and S. Huang, "Research on the prediction method of stock price based on RBF neural network optimization algorithm," *E3S Web of Conferences*, vol. 235, Art. no. 3088, 2021, doi: 10.1051/e3sconf/202123503088.
- [17] P. Saha, N. Gudheniya, R. Mitra, D. Das, S. Narayana, and M. K. Tiwari, "Demand forecasting of a multinational retail company using deep learning frameworks," *IFAC-PapersOnLine*, vol. 55, no. 10, pp. 395–399, 2022, doi: 10.1016/j.ifacol.2022.09.425.
- [18] B. Maleki Shoja and N. Tabrizi, "Customer reviews analysis with deep neural networks for e-commerce recommender systems," *IEEE Access*, vol. 7, pp. 119121–119130, 2019, doi: 10.1109/access.2019.2937518.
- [19] G. Aurélien, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*, 2nd Editio. O'Reilly Media, Inc., 2019.
- [20] U. Norinder and P. Norinder, "Predicting Amazon customer reviews with deep confidence using deep learning and conformal prediction," *Journal of Management Analytics*, vol. 9, no. 1, pp. 1–16, Jan. 2022, doi: 10.1080/23270012.2022.2031324.
- [21] C. Wang, "Efficient customer segmentation in digital marketing using deep learning with swarm intelligence approach," *Information Processing & Management*, vol. 59, no. 6, Art. no. 103085, Nov. 2022, doi: 10.1016/j.ipm.2022.103085.
- [22] B. ul Islam and S. F. Ahmed, "Short-term electrical load demand forecasting based on LSTM and RNN deep neural networks," *Mathematical Problems in Engineering*, vol. 2022, pp. 1–10, Jul. 2022, doi: 10.1155/2022/2316474.
- [23] H.-K. Hwang, A.-Y. Yoon, H.-K. Kang, and S.-I. Moon, "Retail electricity pricing strategy via an artificial neural network-based demand response model of an energy storage system," *IEEE Access*, vol. 9, pp. 13440–13450, 2021, doi: 10.1109/access.2020.3048048.
- [24] H. Nalatissifa and H. F. Pardede, "Customer decision prediction using deep neural network on Telco customer churn data," *Jurnal Elektronika dan Telekomunikasi*, vol. 21, no. 2, pp. 122–127, Dec. 2021, doi: 10.14203/jet.v21.122-127.
- [25] D. Pliszczuk, P. Lesiak, K. Zuk, and T. Cieplak, "Forecasting sales in the supply chain based on the LSTM network: the case of furniture industry," *European Research Studies Journal*, vol. XXIV, no. Special Issue 2, pp. 627–636, Jun. 2021, doi: 10.35808/ersj/2291.

## BIOGRAPHIES OF AUTHORS






**Kassekeyeva Aislu Bisenovna**    received her PhD degree in 2021 in the specialty “Information Systems” named after L.N. Gumilyov, Kazakhstan. Currently he is a senior lecturer at the Department of Information Systems named after L.N. Gumilyov. Her research interests include computational linguistics, data analytics, artificial intelligence, and data mining. She can contact at email: aibike\_7474@mail.ru.






**Sadvakassov Arman Ashatuly**    received a bachelor's degree in technical sciences in specialty 6M070300 - "Information systems" at the Eurasian National University (ENU) named after L.N. Gumilyov, Astana, Kazakhstan, 2022. His research interests include knowledge bases, big data, artificial intelligence and machine learning. He can contact at email: armaxa1403@mail.ru.






**Lamasheva Zhanar Beibutovna**    received a bachelor's degree in technical sciences in specialty 6M070300 - "Information systems" at the Eurasian National University (ENU) named after L.N. Gumilyov, Astana, Kazakhstan, 2022. He is a co-author of 3 publications. His research interests include knowledge bases, big data, artificial intelligence and machine learning. She received the PhD degree in Information systems from Satbayev University, Almaty, Kazakhstan in 2015. Now she is currently working as a Lecturer at Gumilyov Eurasian National University, Astana, Kazakhstan. Her research interests include simulation and data analysis. She can contact at email: zhanarlb@mail.ru.






**Kerimkhulle Seyit Yesilbayuly**    received a doctor of science (economics) in 2003 by specialty 08.00.13 - “Mathematical and instrumental methods of economics” at the Turar Ryskulov Kazakh Economic University, Almaty city. He is a co-author of 29 publications. Currently he is a professor at the Department of Information Systems at the L.N. Gumilyov Eurasian National University. His research interests include business and economics, econometrics, computer science, data mining and sustainability. He can contact at email: kerimkul\_sye@enu.kz.






**Abdrakhmanova Alfiya Zagievna**    received a bachelor's degree in technical sciences in specialty 6M070300 - "Information systems" at the Eurasian National University (ENU) named after L.N. Gumilyov, Astana, Kazakhstan, 2022. He is a co-author of 3 publications. His research interests include knowledge bases, big data, artificial intelligence and machine learning. She received a master's degree in technical sciences in the field of information systems from the Caspian State University of Technology and Engineering named after Sh. Yesenov in 2009. Currently, she is a senior lecturer at L.N. Gumilev Eurasian National University, Department of Information Systems. Her work is related to the field of geoinformation systems and cloud technologies. She can contact at: alfiya\_zagievna@mail.ru.



**Makpal Zhartybayeva Galymbekovna**    received a bachelor's degree in technical sciences in specialty 6M070300 - "Information systems" at the Eurasian National University (ENU) named after L.N. Gumilyov, Astana, Kazakhstan, 2022. He is a co-author of 3 publications. His research interests include knowledge bases, big data, artificial intelligence and machine learning. is PhD, associate professor of the Department Computer and Software Engineering L.N. Gumilyov ENU. Her scientific interests include green technologies, development of mobile robotic systems, geo-radar research, development of an information system for optimizing monitoring of environmental pollution. She can contact at email: makkenskii@mail.ru.



**Oralkhanov Berdibek Oralkhanuly**    received a bachelor's degree in technical sciences in specialty 5B070300 - "Information systems" at the Eurasian National University (ENU) named after L.N. Gumilyov, Astana, Kazakhstan, 2022. His research interests include knowledge bases, big data, artificial intelligence and machine learning. He can contact at email: oralkhanovv@gmail.com.