ISSN: 2690- 912X

Research Article

Journal of Genetic Engineering and Biotechnology Research

Application of Artificial Intelligence to Assess the Risks of Yield Shortage

Davron Sh. Ziyadullaev[1*], Dilnoza T. Mukhamedieva[2], Gulchehra Yu. Yusupova[3], Dilshod E. Eshmuradov[4] and Gulchiroy E. Ziyodullaeva[5]

[1]Tashkent Institute of Irrigation and Agricultural Mechanization Engineers National Research University, Kari Niyazov ave., Tashkent, Uzbekistan

[2]Tashkent State Pedagogical University, Tashkent, Uzbekistan Bunyodkor str.

[3,4,5]Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Amir Temur ave., Tashkent, Uzbekistan

[*]Corresponding Author
Davron Sh. Ziyadullev, Tashkent Institute of Irrigation and Agricultural Mechanization Engineers National Research University, Kari Niyazov ave., Tashkent, Uzbekistan.

Submitted: 2025, Mar 17; **Accepted:** 2025, Apr 01; **Published:** 2025, Apr 10

Citation: Ziyadullev, D. S. Mukhamedieva, D. T., Yusupova, G. Y., Eshmuradov, D. E., Ziyadullaeva, G. E. (2025). Application of Artificial Intelligence to Assess the Risks of Yield Shortage. *J Gene Engg Bio Res, 7*(1), 01-06.

Abstract
The development of the digital economy and related technologies is considered in the article; it opens up many new opportunities to operate with uncertain data in agriculture. This data is collected from remote sensors, satellites, robotics and remote sensing systems. This equipment gets information for twenty-four hours a day in any weather conditions. Based on these data, it is possible to monitor the state of agricultural land and soil, temperature, moisture content, and irrigation regularity. The study aims to assess the risks of yield shortages based on the use of artificial intelligence technology. The main research methods are the theory of semi-structured decision-making; the theory of fuzzy sets and intelligent information technologies created simultaneously with the formalization of professional knowledge and experience of specialists in the field of management; the accumulation and updating of professional knowledge in this area; the development of mathematical models; the processing of empirical knowledge and data and the construction of a mechanism for the logical conclusion of the results of the analysis. The results of the study are the development of approaches to the intellectualization of decision-making systems in assessing the risk of crop shortages, the choice of a rational number of rules and effective values of their membership functions. The relevance and practical significance of the results are determined by the timely prediction of crop shortage risks based on the use of modern information technologies. In designing a fuzzy logic system, the dominant issue is the choice of a rational knowledge base. In this regard, the article discusses the main problems and tasks of intellectualization of information processing systems and ways to solve them.

Keywords: Technology, Intelligence, Smart Home, Risk Assessment, Semi-Structured Decision Making, Fuzzy Set Theory

1. Introduction
The main components of Soft Computing are Fuzzy Logic (FL) and evolutionary algorithms.

Soft Computing components can be applied independently in various areas, such as fuzzy computing, neural computing, and evolutionary computing.

Fuzzy logic offers verbal clarity and interpretability in calculations. It has been successfully implemented in numerous industries, including robotics, stabilization of inverted pendulum systems, complex decision-making and diagnostic systems, data compression, and other areas.

To create a knowledge base presented in a linguistic form or fuzzy digital data, it is necessary to develop a fuzzy model of the system.

The components of Soft Computing - fuzzy logic, neural processing, and probabilistic reasoning complement each other rather than compete. It becomes clear that it is appropriate to use them in combination.

We see that the poor interpretive ability of neural networks, on the one hand, and the difficulty of acquiring knowledge in fuzzy systems, on the other hand, are the reasons for hybridization.
The essence of the neuro-fuzzy approach is the use of the principle

of neural learning to optimize the shapes of membership function curves in fuzzy rules and to minimize the number of rules used, sufficient to achieve the required accuracy.

The combination of rule-based fuzzy systems that model an empirical, intuitive strategy used by a person when making decisions and genetic algorithms that allow a global search for the optimum of a wide range of functions (response surface) makes it possible to create an efficient, robust adaptive control system.

Often, membership functions in fuzzy rules of knowledge bases of fuzzy systems are represented as fuzzy numbers of the LR-type, for example, in the form of a trapezoid, triangles, etc. Gradient methods used to correct fuzzy knowledge bases, i.e. determine the values of centers and types of membership functions do not justify themselves. An effective tool, in this case, is the genetic algorithm.

The combination of fuzzy logic and genetic algorithm allows us to optimize the fuzzy knowledge base by determining the optimal number of rules in the knowledge base and the optimal values of the centers and types of membership functions. In this case, the genetic algorithm is used to build a matrix of relations and membership functions of the designed fuzzy system.

In turn, fuzzy set theory can be used in the integration of fuzzy logic and genetic algorithms to improve the behavior of genetic operators and genetic algorithms in general. It is possible to create fuzzy tools to improve the efficiency of the genetic algorithm, that is, to develop fuzzy genetic algorithms.

Integration of a genetic algorithm with a neural network also gives effective results. It is known that one of the main tasks in the development of artificial neural systems is the choice of an appropriate learning method for setting the neural network parameters (weights, thresholds, etc.). The best-known method is the backpropagation algorithm. However, there are some difficulties with backpropagation. First, the training efficiency significantly depends on the initial set of neural network weights, determined randomly. Second, backpropagation, like any gradient method, does not allow us to avoid local minima. Third, if the training rate is too low, it takes a long time to find a solution. Fourth, backpropagation requires activation functions to be differentiable. This condition is not met for many types of neural networks. Genetic algorithms used to optimize many problems when "strong" methods cannot find a good solution are successfully used to train neural networks, being free from the above disadvantages.

Data mining plays an important role in information systems lifecycle management, including data processing, information flow, and knowledge management. Data mining and artificial intelligence technologies are already being used in various sectors of the national economy. In medicine, based on the processing of a large amount of uncertain data, they allow making a timely diagnosis with high accuracy. These technologies are widely used in everyday life. In industry, artificial intelligence makes it possible to fully automate harmful and dangerous production. AI-powered smart home technology optimizes alarms, makes purchases, and even makes purchases on behalf of an employee. These technologies are becoming increasingly important in agriculture.

Forecasting uses data mining and artificial intelligence technologies. As shown in machine learning technologies have made it possible to obtain accurate forecasts of potential drought risks in eastern Australia [1-3]. In similar results were obtained for the conditions of Pakistan using a machine-learning model [4,5]. The ongoing analytical analysis makes it possible to use data mining and artificial intelligence technologies in making managerial decisions to reduce the effects of climate risks and manage crop yields. In managing water resources in the agro-industrial sector, the development of mathematical models plays an important role and requires significant efforts. Accurate estimation of evapotranspiration is a complex process and is essential for crop resource management and the efficient operation of irrigation systems.

Data mining and artificial intelligence technologies make it possible to identify weeds in crops. A new method based on machine learning and hyperspectral imaging methods was developed in to recognize crop and weed species [5,7]. The proposed method allows accurate identification of various types of weeds; this makes it possible to achieve a certain economic effect and reduce the level of herbicidal treatment of crops.

Summarizing the data on data mining and artificial intelligence technologies used in the agro-industrial sector, we can highlight the general characteristics of the agro-industrial complex. Data mining and artificial intelligence technologies used in the agro-industrial complex have a number of significant features, namely [8,9].

• Technical solutions, primarily software-hardware tools for performing certain tasks in the agro-industrial sector in predicting the development of agriculture, depending on various factors (climate, soil conditions, rainfall, and market prices). Often, data mining and artificial intelligence technologies are used in conjunction with robotics, the selection of optimal tools, and the recognition of obstacles and objects.
• Decisions made in agriculture, or in the development of an optimal strategy for managing the agro-industrial complex, functioning in livestock houses or open areas, which makes it necessary to orientate in space, often with the pattern recognition (of various unsorted objects);
• Operating with large amounts of data in the intellectual analysis of the development strategy of the agro-industrial complex;
• Results of these technologies are used when solving intellectual problems in the agro-industrial sector.

The introduction of these technologies will also reduce the employment of people in industries that are hazardous and harmful to humans and animals, primarily when working with pesticides, spraying plants and cleaning manure. This, in turn, will increase the attractiveness of the industry for young professionals.

Artificial intelligence provides accurate forecasts of profitability, price and market risks, increases efficiency in making managerial decisions, and the knowledge level. Quite often, investors from the agro-industrial sector are deterred by high risks of yield shortage, sharp price fluctuations, etc.

The next chapter presents methods and approaches for assessing the risks of crop shortages as many external factors affect the reduction in crop yields. Experts present these factors (weather conditions and water supply) in a fuzzy form.

2. Materials and Methods

The study aims to assess the risks of crop shortages based on artificial intelligence technology. The main objectives of the work are the development of approaches to determine various options of the impact of water supply factors and weather conditions on the reduction in cotton yield during sowing, growing season, and harvesting period; to intellectualization of decision-making systems when assessing the risk of yield shortages, choosing a rational number of rules and effective values of their membership functions.

The methodological basis of the study is a fuzzy approach to managing the development of artificial intelligence technology, including the analysis and practical generalization of the essence when making semi-structured decisions. With the analysis and synthesis methods used, the management structure of artificial intelligence technology was analyzed, and approaches to determining various options for influencing the reduction in cotton yields were considered.

Potential yield is determined by the following formula (1)

$$\overline{Y}_{kij} = \left(\sum_{s=1}^{m} \mu^s Y_{kij} Y_{kij}^s / \sum_{r=1}^{m} \mu^r Y_{kij}\right)(1 + w_{ki}), \qquad (1)$$

where is the coefficient of recovery of crop shortage due to adverse weather conditions and water supply (2).

The recovery factor is expressed as follows

$$\begin{aligned} w_{ki} = {} & 0,01\rho_1\left(1-\sum_{s=1}^{m} \mu \Pi_{ki}^s \Pi_{ki}^s / \sum_{r=1}^{m} \mu \Pi_{ki}^r\right)\cdot \\ & \cdot\left(1-0,3\sum_{s=1}^{m} \mu BO_{ki}^s BO_{ki}^s / \sum_{r=1}^{m} \mu BO_{ki}^r - 0,7\sum_{s=1}^{m} \mu B_{ki}^s B_{ki}^s / \sum_{r=1}^{m} \mu B_{ki}^r\right)+ \\ & +0,01\rho_2\left(1-\sum \mu B_{ki}^s B_{ki}^s / \sum_{r=1}^{m} \mu B_{ki}^r\right) + 0,01\rho_4\left(1-\sum_{s=1}^{m} \mu BO_{ki}^s BO_{ki}^s / \sum_{r=1}^{m} \mu BO_{ki}^r\right)\cdot \\ & \cdot\left(1-0,4\sum_{s=1}^{m} \mu B_{ki}^s B_{ki}^s / \sum_{r=1}^{m} \mu B_{ki}^r - 0,2\sum_{s=1}^{m} \mu \Pi_{ki}^s \Pi_{ki}^s / \sum_{r=1}^{m} \mu \Pi_{ki}^r\right)+ \\ & +0,01\rho_3\left(1-\sum_{s=1}^{m} \mu \text{УБ}_{ki}^s / \sum_{r=1}^{m} \mu \text{УБ}_{ki}^r\right). \end{aligned} \qquad (2)$$

Here:
P_{kij} - is the sown area of the cotton crop;
Y_{kij} - is the cotton yield;
μY_{kij} - is the membership function for cotton;
C_{kij} - is the breeding cotton variety
N_{kij} - is the amount of nitrogen introduced to cotton plant;
μN_{kij} - is the membership function for the amount of nitrogen introduced to cotton plant;
μN_{kij} - is the membership function of the introduced nitrogen;
BO_{ki} - is the water availability;
μBO_{ki} - is the water availability membership function;
Π_{ki} - are the weather conditions of the sowing season;
$\mu \Pi_{ki}$ - is the membership function Π_{ki};
B_{ki} - are the weather conditions of the growing season;
μB_{ki} - is the membership function B_{ki};
УБ_{ki} - are the weather conditions of the harvesting period;
$\mu \text{УБ}_{ki}$ - is the membership function УБ_{ki}.

Thus, we have described various options for the influence of water supply factors and weather conditions on the decrease in cotton yield during the sowing, growing season, and harvesting period.

The predicted yield, considering the water supply and weather conditions of the current year in a fuzzy environment, is determined by the following expression (3)

$$Y_{kij}^{\Pi} = \left(\sum_{s=1}^{m} \overline{Y}_{kij}^s \mu Y_{kij}^S / \sum_{r=1}^{m} \mu Y_{kij}^r\right)(1 - v_i), \qquad (3)$$

where v^i - is the prediction coefficient determined by formula (4):

$$\begin{aligned} v_i = {} & 0,01\rho_1\left(1-\sum_{s=1}^{m} \mu \Pi_i^s \Pi_i^s / \sum_{r=1}^{m} \mu \Pi_i^r\right)\cdot \\ & \left(1-0,3\sum_{s=1}^{m} \mu BO_i^s BO_i^s / \sum_{r=1}^{m} \mu BO_i^r - 0,7\sum_{s=1}^{m} \mu B_i^s B_i^s / \sum_{r=1}^{m} \mu B_i^r\right)+ \\ & +0,01\rho_2\left(1-\sum_{s=1}^{m} \mu B_i^s B_i^s / \sum_{r=1}^{m} \mu B_i^r\right)+ \\ & +0,01\rho_4\left(1-\sum_{s=1}^{m} \mu BO_i^s BO_i^s / \sum_{r=1}^{m} \mu BO_i^r\right)\cdot \\ & \left(1-0,4\sum_{s=1}^{m} \mu B_i^s B_i^s / \sum_{r=1}^{m} \mu B_i^r - 0,2\sum_{s=1}^{m} \mu \Pi_i^s \Pi_i^s / \sum_{r=1}^{m} \mu \Pi_i^r\right)+ \\ & +0,01\rho_3\left(1-\sum_{s=1}^{m} \mu \text{УБ}_i^s \text{УБ}_i^s / \sum_{r=1}^{m} \mu \text{УБ}_i^r\right). \end{aligned} \qquad (4)$$

Currently, this approach has a great future in the agro-industrial complex and agriculture, since it will lead to the digitalization of the industry.

The land organization is preceded by a detailed study of the territory based on observation materials of soil, erosion, reclamation, geobotanical, water management, and land management and other types of surveys. Based on this information, a qualitative characteristic of agricultural land is compiled.

To solve the problems of transformation (relocation) and land improvement, it is necessary to use a soil map with detailed characteristics of each soil type in terms of humus content and population density.

Studies were conducted in on the soil evaluation and the economic assessment of lands [3,6]. It is possible to use these materials in the land organization. In this case, the starting point can be a land cadastral map, which shows agricultural land and all types of soil and assesses land quality classes, identified based on the economic assessment results. Each class includes soil varieties and their complexes, which differ from each other by 10 points. Since the economic assessment is conducted, as a rule, according to a 100-point system, 10 assessment classes can be established, highlighting the best, average, and worst lands.

3. Results

The task of the experiment was to test the possibility of identifying nonlinear dependencies using the proposed neuro-fuzzy network and to compare this new method with the traditional method of neural identification [8,14]. The experimental procedure was as follows.

The nonlinear object was set by the reference model in the form of an analytical dependence. Observing the graph of this dependence, the expert formed a fuzzy knowledge base, on which the corresponding neuro-fuzzy network was built. The training was conducted using "input-output" pairs, generated from the reference model, uniformly covering the entire range of changes in the input variable, and lasted until the dependency graph produced by the neuro-fuzzy network became close enough to the reference model.

In the experiment, a second-order reference object was used (5):

$$Y = \overline{Y}\,(1 - 0.01\rho_1(1 - x1_i)(1 - 0.3x2_i - 0{,}7x3_i) + 0.01\rho_2(1 - x3_i) + \\ + 0.01\rho_4(1 - x2_i)(1 - 0.4x3_i - 0.2\tilde{o}1_i) + 0.01\rho_3(1 - \tilde{o}4_i)), \quad (5)$$

here
Y- is the cotton yield;
$\overline{Y}$ - is the potentially-possible productivity;
x_1 - are the weather conditions during sowing;
x_2- is the water supply;
x_3- are the weather conditions during the growing season;
x_4- are the weather conditions during harvesting.

Here, the impact of factors influencing the decrease in yield occurs due to weather conditions at p_1 % sowing, p_2 %, vegetation, p_3% harvesting, and p_4% water supply.
Based on this, it is easy to describe the behavior of the knowledge base:

IF X1=H AND X2=H AND X3=H AND X4=H WITH WEIGHT 0.5

OR X1=C AND X2=H AND X3=H AND X4=H WITH WEIGHT 0.5

THEN У=H

OR X1=H AND X2=H AND X3=H AND X4=C WITH WEIGHT 0.09

OR X1=H AND X2=H AND X3=H AND X4=B WITH WEIGHT 0.09

OR X1=H AND X2=H AND X3=C AND X4=H WITH WEIGHT 0.09

OR X1=H AND X2=C AND X3=H AND X4=H WITH WEIGHT 0.09

OR X1=C AND X2=H AND X3=H AND X4=C WITH WEIGHT 0.09

OR X1=C AND X2=H AND X3=C AND X4=H WITH WEIGHT 0.09

OR X1=C AND X2=C AND X3=H AND X4=H WITH WEIGHT 0.09

OR X1=B AND X2=H AND X3=H AND X4=H WITH WEIGHT 0.09

OR X1=B AND X2=H AND X3=H AND X4=C WITH WEIGHT 0.09

OR X1=B AND X2=H AND X3=C AND X4=H WITH WEIGHT 0.09

OR X1=B AND X2=C AND X3=H AND X4=H WITH WEIGHT 0.09

THEN У=HC

Experts chose the membership functions of fuzzy terms used in this knowledge base.

In designing a fuzzy logic system, the dominant issue is the choice of a rational knowledge base, or rather, a rational number of rules and effective values of their membership functions [12-16]. There are various ways of forming fuzzy knowledge bases: obtaining knowledge from an expert, a method based on the use of mathematical models, a neuro-fuzzy approach, etc. The main criteria for this are the absence of redundancy of fuzzy rules, inconsistency, and defective, false knowledge. Generally, designers of fuzzy logic systems try to get an acceptable solution with a minimum number of fuzzy rules. This is especially important from the point of view of the effective implementation of fuzzy hardware and fuzzy software of the system being designed. One of the ways to solve this problem, i.e. designing an efficient network of fuzzy rules, is an approach based on the use of neural networks and evolutionary algorithms.

4. Discussion

R. Aliev believes that the future in our life stands for digitalization, in particular, for artificial intelligence, robotics, and nature-like technologies such as fuzzy logic [17]. In his opinion, fuzzy logic provides verbal impressibility and interpretability of calculations, and therefore the main task should be to teach to learn and to think. Therefore, it is necessary to use the new digital capabilities of artificial intelligence for educational purposes. To do this, first, it is necessary to train qualified specialists in digitalization in agriculture with an emphasis on Soft Computing.

Currently, the issue of using Soft Computing components independently is discussed in the scientific literature (fuzzy computing, neural computing, and evolutionary computing) [16-18].

To create a knowledge base, presented in a linguistic form or the form of fuzzy digital data, we need to have a fuzzy model of the system. A necessary condition for identifying a non-linear object based on fuzzy logic is the presence of IF-THEN rules that connect linguistic estimates of input and output variables [10,11]. Previously, in it was assumed that the IF-THEN rules are generated by an expert who knows the object well. However, what if there is no such expert? In this case, there is a necessity to generate IF-THEN rules, i.e. it is necessary to build a fuzzy knowledge base from the available experimental data.

The article proposes the transformation of experimental information learned from experts involved in cotton growing, into fuzzy knowledge bases. This has proven to be a useful method of processing data in agriculture, where decision-makers prefer to use transparent and easy-to-interpret verbal rules instead of strict quantitative ratios. At that, the criterion for the quality of the derived patterns is the closeness of the results of linguistic approximation and the corresponding experimental data.

This is especially true in modeling the potential yield of agricultural products since data in this area is not always presented in a certain way. Generally, membership functions in fuzzy rules of knowledge bases of fuzzy systems are represented as fuzzy numbers. Gradient methods to correct fuzzy knowledge bases, i.e. to determine the values of centers and types of membership functions, do not justify themselves. In this regard, the article proposes methods and approaches for determining various options for influencing the reduction in cotton yields of water supply factors and weather conditions during the sowing, vegetation, and harvesting period. With these approaches, a formula for finding the predicted yield is presented.

5. Conclusion

The three technologies discussed in this article, which are closely related to artificial intelligence, are becoming increasingly prominent in the field of agriculture. This rise is attributed to the fact that automating agricultural processes effectively addresses the challenges faced in the agro-industrial sector; they allow speeding up the process of growing the required volumes of crops and food without the risk of reducing the quality of the final product.

An attempt to develop and implement models of weakly formalized processes with fuzzy initial information, expressed in the form of logically justified linguistic statements was one of the main objectives of this study [20,21]. In the research, hybrid intelligent models for constructing fuzzy models of poorly formalized processes were developed. The possibilities of applying the methods of fuzzy mathematics in cotton growing were investigated. The best conditions for their application were determined and substantiated. A technique was created that contributes to solving applied problems of assessing the risk of crop shortage in cotton growing based on the fuzzy set theory. A knowledge base was developed and a Mamdani-type fuzzy inference model was created to assess the risk of yield shortage. A method was developed for representing linguistic knowledge about the identification object in the form of a special neuro-fuzzy network.

Despite the successes achieved, many tools for the mathematical apparatus for the theory of fuzzy sets and fuzzy inference require further development since they have not yet reached the level of traditional mathematics apparatus. Developing the fuzzy-set approach will improve the theoretical and applied apparatus for developing efficient methods for solving hard-to-formalized problems with fuzzy parameters. This will significantly expand the application of this approach in various fields (scientific, technical, and social).

References

1. Nabokov VI, Nekrasov KV, Zueva ON, Donskova LA (2016). Development of logistics systems in the agro-industrial complex. *Agrarian Bulletin of the Urals*. 2016. Ye. 12 (154): pp. 102–104.
2. Nabokov VI, Skvortsov YeA, Nekrasov KV (2018). Bulletin of VIESH. *Agrarian Bulletin of the Urals Ye. 04* (33).
3. Forsyth, DA., Pons, J. (2004). Computer vision. Modern approach. YeDP Williams.
4. Fedorenko, VF., Chernoivanov, VI., Goltyapin, V. (2018). World trends in the intellectualization of agriculture: a scientific analytical review YeDPR of informagrotech.
5. Amatya, S., Karkee, M., Gongal, A., Zhang, Q., Whiting, MD. (2015). Biosystems Engineering. J. Ye 146.
6. Dutta, R., Smith, D., Rawnsley, R. (2015). Bishop-Hurley. Computers and Electronics in Agriculture. J. Ye 111.
7. Luger, DF. (2005). Artificial Intelligence. Strategies and methods for solving complex problems.
8. Siegel, Ye. (2018). Calculate the future. Who clicks, buys, lies or dies. YeDP Alpina Publisher.
9. Denning, PJ., Lewis, TG. (2017). Exponential Laws of Computing Growth. Communications of the ACM. J. Ye 60.
10. Sotvoldiev, D., Mukhamedieva, DT., Juraev, Z. (2020). Journal of Physics: Conference Series.
11. Ziyadullaev, DSh., Mukhamedieva, DT., Ziyodullaeva, GYe. (2018). Development of mathematical model of lesson schedule formation system. *Journal of Advanced Research in Dynamical and Control Systems. 10* (14).
12. Yager, R.R., Zadeh, L.A. (1994). Fuzzy sets, neural networks and Soft Computing. VAN Nostrand Reinhold. New York, 440p.
13. Aliev, R.A., Barak, D., Chew, G. (1994). Soft Computing: Fuzzy Logic. Neural Networks and Distributed Artificial Intelligence. F.Amin zadeh. Jamshidi M. (Eds.), PTR Prentice Hall Englewood Cliffs, New Jer sey, 301p.
14. Zurada, Y.M., Marks, R.J. Robinson, C.Y. (1994). Computational Imitating Life Piscataway. NJ:IEEE press. 448p.
15. Pearson, D.W., Steel, N.C., Albrecht, R.F. (1995). Artificial Neural Nets and Genetic Algorithms. Proc. of the Inter Conference in Ales, France.552p.
16. Proceeding of the Second European Congress on Intelligent Techniques and Soft Computing, Aachen, 1994, 1750p.

17. Aliev, R.R. (1997). Soft Computing and MIQ enhancement. Scientific Paper of ASNA No. 1.
18. Aliev, R.A. Kenarangui. R. (1994). Applications of Fuzzy Systems University press of Tabriz, Tabriz. 420p.
19. Ziyadullaev, D., Mukhamedieva, D., Khujamkulova, Kh., Teshaboyev, M., Ziyodullaeva, G. (2024). Solving diabetes diagnosis problems using machine learning. BIO Web of Conferences 2024, 121, 01003.
20. Ziyadullaev, D., Muhamediyeva, D., Khujamkulova, Kh., Abdurakhimov, D., Maksumkhanova, A., Ziyodullaeva, G. (2024). Ensemble data mining methods for assessing soil fertility. E3S Web of Conferences, 2024, 494, 02013.
21. Inoyatova, M., Ziyadullaev, D., Muhamediyeva, D., Aynaqulov, Sh., Ziyaeva, Sh. (2024). Data mining for assessing soil fertility. E3S Web of Conferences. 494, 02012.