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Development of a decision-making module in the field of real estate rental using machine learning methods

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ABSTRACT

The research is aimed at developing a prototype of a decision support information system for managers of a company operating in the real estate rental industry. The system provides tools for data analysis, the use of mathematical models and expert knowledge to solve complex problems. The work analyzes the practical aspects of the design and use of decision support systems and formulates the requirements for the functionality of the system being developed. The Python programming language was used for implementation. The prototype includes machine learning models, expert systems, user interface and reports. Linear regression, data clustering density-based spatial clustering of applications with noise (DBSCAN) and backpropagation methods were implemented to train the classifying perceptron. The developed tool represents a significant contribution to the field of decision support, providing unique analysis and forecasting capabilities in the dynamic real estate rental environment. This prototype is an innovative solution that promotes effective management and strategic decision making in complex real estate business scenarios.

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1. INTRODUCTION

In modern conditions of increasing volumes of information and increasing complexity of tasks in enterprise management, especially in the field of rental real estate [1]–[3], the relevance of developing decision support systems (DSS) [4], [5] becomes undeniable. The growth in the amount of data every year acquires a magnitude that exceeds the capabilities of human processing [6]. Consequently, there is a rapid need to develop more tools to manage data [7] and make better decisions in specific areas. Decision support systems are an important tool that can help organizations manage vast amounts of information and make informed decisions. Automation of data analysis, the use of intelligent algorithms and models [8], as well as the provision of intuitive reports and graphs-all this allows you to effectively manage data [9], identify risks, predict trends and adapt to changes in the external environment. In this research work, the focus is on developing a prototype information system for decision support in the field of real estate rental using machine learning methods [10]–[12]. The goal of the work is to create a module capable of optimizing information processes and providing more efficient enterprise management. The object of the study is the developed prototype, and the subject is the theoretical foundations, design methods and effective implementation of a decision support system taking into account real estate rental data. Using concepts from data science [13]–[15] and machine learning processes [16]–[18], the work covers a wide range of problems, such as a system for assessing the solvency of a tenant [19], systematizing the visualization of information for decision makers, and building mathematical models, reflecting important factors for the company. The presented tasks are aimed at achieving the goal of the work, and their analysis and testing in real conditions allow us to evaluate the effectiveness of the developed module of the decision support system in the field of real estate rental.

During the study, the following tasks were identified and solved: development of a system for assessing the solvency of the tenant, based on the analysis of previous data; systematization of information visualization for decision makers; construction of mathematical models reflecting significant factors in the field of rental real estate. End user access to the system data storage was also provided, which facilitates wider use of the developed module. An important aspect of the work is the automation of report generation, which greatly simplifies the decision-making process [20]–[22] and ensures a more rapid response to changes in the external environment. An analysis of the prototype’s performance in real conditions confirms its effectiveness and potential in improving management decisions in the field of real estate rental [23]–[25]. Thus, this scientific work represents an important step in the development of decision support tools specifically focused on the real estate rental industry and contributes to the field of application of machine learning methods for optimizing business processes. In today's challenging business environment, where the speed and accuracy of decision making become critical, the development and successful implementation of a decision support information system using machine learning methods acquires strategic importance. The prototype presented in this work goes beyond traditional approaches by providing integrated tools for analysis, visualization and forecasting in real estate rental environments. Decision makers now have a powerful tool that allows them not only to effectively manage data, but also to quickly respond to changing market conditions. Future research prospects may include expanding the functionality of the prototype, integrating with additional data sources, and optimizing machine learning algorithms to improve the accuracy and adaptability of the system. This approach to innovative management in the rental property industry opens up new perspectives for businesses seeking to leverage advanced technology to improve their competitiveness and operational efficiency.

We aim to address the problem of managing the increasing volume and complexity of data in the real estate rental market, which challenges traditional DSS that lack efficiency in real-time processing and advanced analytics. Existing solutions, including basic DSS and manual data analysis, fall short in scalability and adaptability, particularly in dynamic market conditions. Our research seeks to overcome these constraints by developing a prototype DSS that integrates advanced machine learning techniques to enhance predictive accuracy and operational efficiency. By doing so, we intend to provide real estate managers with a robust tool capable of sophisticated data management and predictive insights, thus significantly improving decision-making processes in the industry.

Our research primarily enhances the existing decision support system models by integrating machine learning methods, specifically focusing on the use of linear regression and density-based spatial clustering of applications with noise (DBSCAN) algorithms in the real estate rental market. This integration offers a more dynamic approach to data analysis, facilitating more accurate and efficient decision-making processes compared to traditional models that rely heavily on static data or simpler predictive analytics. Previous research in this domain has primarily concentrated on the functional aspects of decision support systems without a significant emphasis on the integration of advanced machine learning techniques. For instance, prior studies have often addressed the theoretical design and basic application of decision support systems within various business sectors. But have not deeply explored the enhancement of these systems through sophisticated machine learning strategies that deal with real-time data processing and prediction in complex scenarios such as real estate rentals.

2. METHOD

During the research process, it was revealed that decision support systems can be based on various artificial intelligence methods, depending on the needs and goals of a particular system. Among the common artificial intelligence methods used in decision support systems, expert systems occupy a special place. Expert systems use artificial intelligence to simulate the decision-making process of a human expert. They typically include a knowledge base and a set of rules or algorithms that allow the system to reason and make decisions based on the learned knowledge. Artificial intelligence techniques are an effective means of supporting decision-making in organizations because they can help decision makers quickly analyze complex data and identify patterns that are not always obvious to humans. It is important, however, to use artificial intelligence techniques responsibly, given their potential biases or lack of accuracy, and to pay attention to the ethical implications of using artificial intelligence in decision making.

In the modern world, increased programmer productivity is partially achieved due to the fact that part of the intellectual load is placed on computers. The use of "artificial intelligence" is one of the ways to achieve maximum progress in this area, where computers not only perform similar and repetitive operations, but are also capable of learning. The creation of full-fledged “artificial intelligence” opens up new horizons of development for humanity. The main object of research is human thinking abilities and methods of their technical implementation. Technical implementation is carried out using machine learning and artificial neural networks. Machine learning is a method of creating artificial intelligence that involves teaching a computer to recognize patterns and make predictions based on data. Machine learning algorithms can be used in decision support systems to predict outcomes or make recommendations based on historical data. Neural networks, in turn, are a machine learning algorithm based on the structure of the human brain. They can be used in decision support systems to process and analyze large volumes of data, as well as to make forecasts or provide recommendations based on this information.

Thus, expert systems play a significant role in the field of artificial intelligence and decision support by providing effective tools to imitate human expert thinking. However, when developing and using such systems, their limitations, potential biases, and ethical considerations must be taken into account. In addition, for the successful development of a prototype decision support information system (DSIS), the use of data mining, also known as data mining, is being considered. Various definitions of this method include the process of discovering non-trivial and useful patterns in databases, extracting, exploring and modeling large volumes of data in order to discover unknown structures and obtain practical business benefits. It is noted that data mining is the process of identifying patterns and trends in large data sets, using pattern recognition techniques and other statistical and mathematical methods. The term data mining gets its name from the search for valuable information in large databases and the analogy with mining ore. Both processes require sifting through large amounts of raw material or intelligent exploration to find valuable knowledge. As a result of the analysis of scientific sources, it is concluded that the key solution for the development of DSS is the creation of an expert system module with artificial intelligence algorithms. This module is considered as the core of the DSS. In addition, it is proposed to develop a separate module for data mining, including algorithms for data clustering and building a mathematical model. At the stage of developing an information DSS, systematic updating of data in the information repository is provided. To solve this problem, it is also proposed to create a separate module in Figure 1.

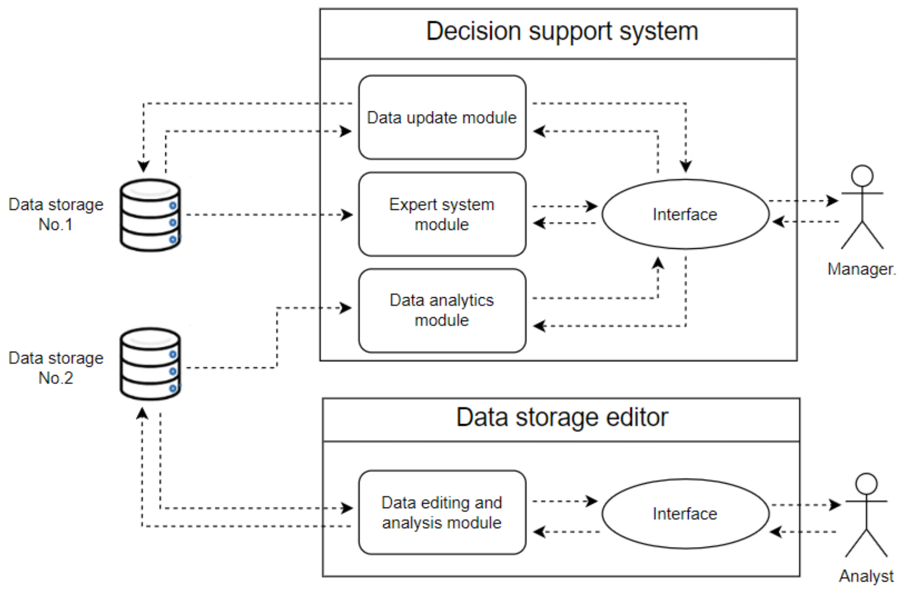

Figure 1. Structure of information DSS

When implementing a DSIS, two data warehouses were created. The first of them contains information about rental transactions between the company and tenants, while the second store stores competitor data entered by the analyst. The process of processing transaction data is carried out in the expert system (ES) module. This module calculates the history score for each tenant based on the data provided. If the new tenant's data is not in the data warehouse, then his information is processed through an artificial neural network. The processed data is visualized and at the request of the manager, an intelligent report is generated. The data mining module accepts input data about competitors, subjecting them to appropriate processing and constructing a mathematical model.

3. RESULTS AND DISCUSSION

An expert system in the development of a DSS is a system that imitates the abilities of an expert in the field of real estate rental services, which uses the artificial intelligence method. Such a system uses a combination of rules and inference algorithms to make decisions that are based on the knowledge acquired by the expert. In this work, a software implementation of the expert system was carried out in conjunction with an artificial neural network in Figure 2.

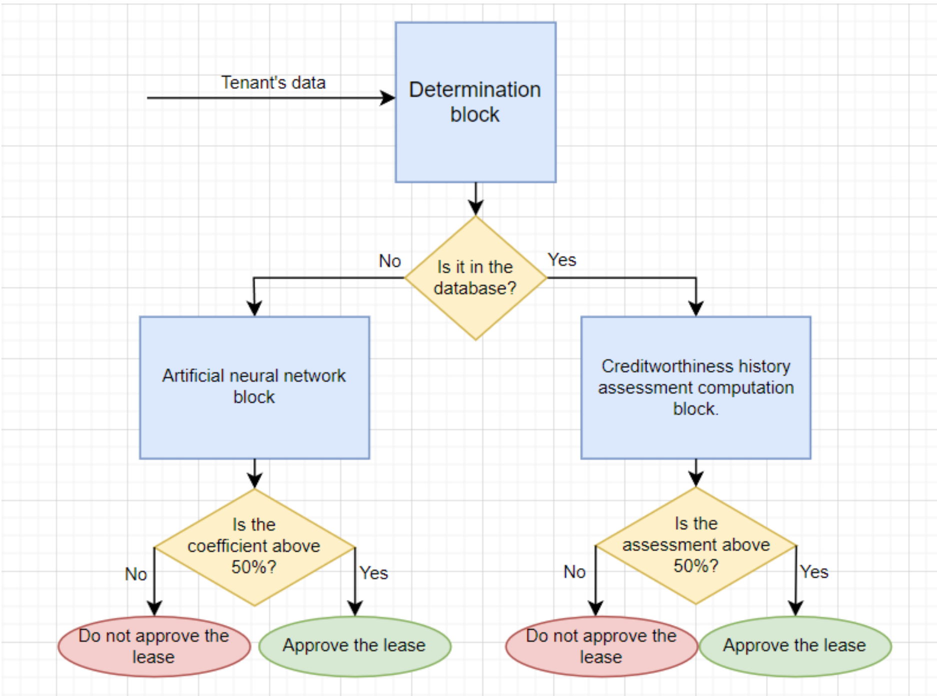

Figure 2. Expert system diagram number 1

At the beginning of the process, the first input signal is the tenant data through the definition block. This block checks the presence of a tenant in the database and analyzes its solvency history. If the tenant's data is present in the database, then the block calculates an assessment of his solvency history using the formula: the number of months of stable solvency is divided by the total number of months of rent. The result obtained is multiplied by 100, which leads to the conclusion of an assessment of the tenant's solvency as a percentage. Further, the operating algorithm follows the following conditions: if the assessment of the tenant's solvency is below 50%, then the history is considered unfavorable, and the tenant is defined as undesirable. If the tenant's solvency score is greater than or equal to 50%, then the history is considered good, and the tenant is determined to be desirable. If the tenant's data is not in the database, the remaining input data is sent through an artificial neural network. The network output is also multiplied by 100, resulting in the solvency ratio as a percentage. In this case, the system is based on similar conditions: if the obtained solvency ratio from the neural network block is below 50%, then the tenant is considered undesirable. And if the assessment of the tenant's solvency is higher than or equal to 50%, then the tenant is determined as desirable. During the work, it was also decided to develop an expert system for analyzing data from two incoming tenants as shown in Figure 3. The need for this system is due to the complexity of making a decision when choosing between two potential tenants. In this way, the system provides support to the decision maker in making the optimal decision in a difficult situation.

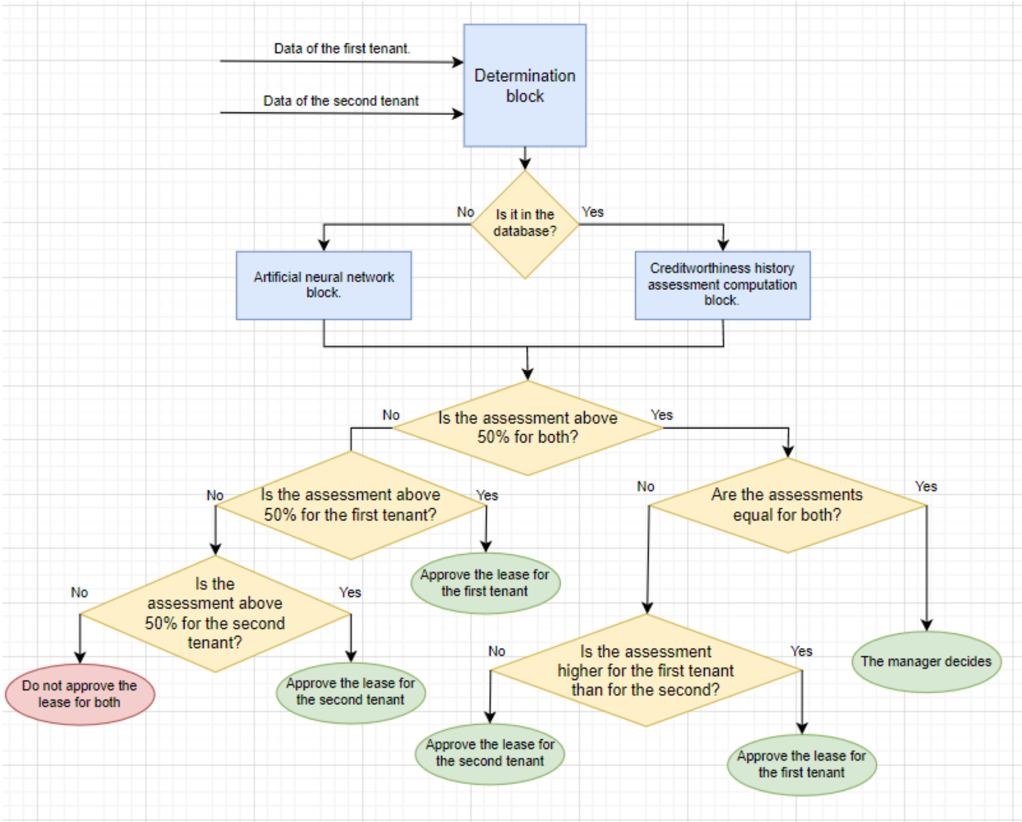

Figure 3. Scheme of expert system number 2

In the expert system, the artificial neural network performs the scoring function, which is a method for assessing the risk or likelihood of undesirable events occurring, such as non-payment of housing services, damage to real estate or violation of the terms of the contract during the rental process. To ensure maximum efficiency of the neural network, it is necessary to train it. The artificial neural network training process involves generating a tenant data table. Each row in this table contains information about a specific tenant, as well as a decision made by a rental property expert based on his experience. The following six tenant characteristics were used to form decisions: tenant salary, rental price, tenant gender, tenant age, number of adults, number of children. Thus, the scoring being developed is based on statistical analysis of historical data and uses a model in the form of a perceptron. In a perceptron as shown in Figure 4, connections between a neuron and input signals have certain weights.

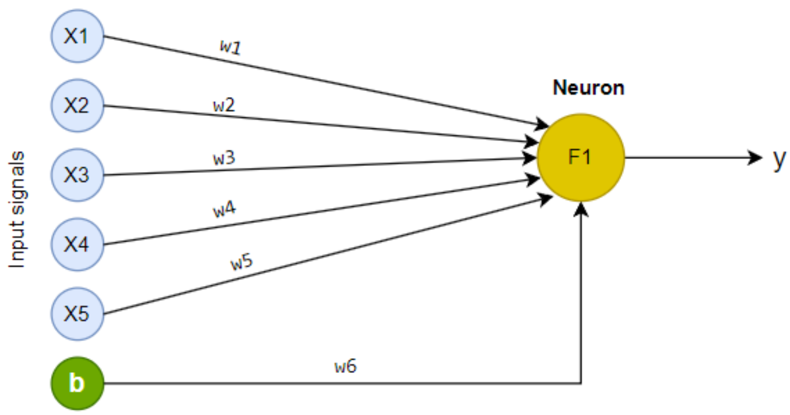

Figure 4. Diagram of a neural network with one neuron

Connections between neurons have certain weights. First, all inputs are summed taking into account the weight of each connection, so the sum is formed. The value of the resulting sum is then passed through the neuron activation function. For a network with a small number of layers, it was customary to apply the logistic function (1) as the activation function of each neuron.

$$Sigmoid(x) = \frac{1}{1+e^{-x}} \tag{1}$$

where $Sigmoid(x)$ is the logistic function, e is the exponent, x is the input signal. The logistic function converts any input value into a range between zero and one as shown in Figure 5, which can be interpreted as the probability that a given sample belongs to the desirable or undesirable class. This function has a simple and smooth graph, making it easier to train and providing the non-linearity needed for most machine learning problems. Due to its nonlinearity, the logistic function allows the network to process and interpret complex dependencies between input data and output classes. Thus, the logistic function is widely used in neural networks, especially in cases of binary classification and in a small number of layers, since it is easy to implement and gives a good result.

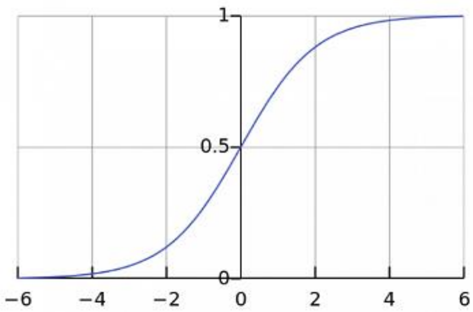

Figure 5. Geometric image of the logistic function

To avoid classification errors, neural networks use an additional input, a threshold value for the offset of the separating hyperplane. In English literature it is called Bias (b). As a rule, it is equal to one. The operation scheme of each neuron includes connection weights, which are selected randomly in the range from -0.5 to 0.5. In order to train a neural network, its structure, initial connection weights and also input signals were created. The input signals are observations that are fed to the input of the neural network and each observation has a desired required value. Each input represents specific tenant data:
X_1 – The difference between the tenant's salary and the rental cost divided by 100,000.
X_2 – Gender of the tenant (male is given by one, female by zero).
X_3 – Tenant's age divided by 100.
X_4 – Number of adults who will live in the apartment.
X_5 – Number of children who will live in the apartment.

Thus, the specific observation input signals are supplied to the network input: X_1, X_2, X_3, X_4, X_5, b. The operation of a single-layer perceptron can be described by one mathematical formula. Where all inputs are summed up taking into account the weight of each connection. Next, the generated amount passes through the activation function in the form of a logistic function through exponent (2):

$$y = \frac{1}{1+e^{-(W_1*X_1-W_2*X_2+W_3*X_3-W_4*X_4-W_5*X_5+W_6*b)}} \tag{2}$$

where y is output value of the neural network, e is exponent, W is weights between input signals and neuron, X is input signals, and b is threshold value. The resulting y value is the output of the neural network. The work of the perceptron is carried out in such a simple and understandable way. The perceptron is trained as follows. Knowing the current response d for the input vector, the error committed by the neural network is calculated. This error is calculated as the difference between the output value of the neural network and the desired required value (3):

$$E = y - d \tag{3}$$

where E is error of the neural network, y is output value of the neural network, d is desired required value. The learning process is a process of adjusting weights, which occurs in the opposite direction. Starting from the very last layer and going up to the very first. Having calculated the error committed by the neural network and having an activation function for the neuron output, the process of adjusting the weights begins. According to backpropagation algorithms, the local gradient for the last output neuron is first calculated. The local gradient is calculated using formula (4):

$$Q = E * y * (1 - y) \tag{4}$$

where Q – local gradient, E – error of the neural network, y – output value of the neural network. Next, all the necessary values were obtained to correct the weights for the neuron (5):

$$\begin{aligned} W_1 &= W_1 - L * Q * X_1 \\ W_2 &= W_2 - L * Q * X_2 \\ W_3 &= W_3 - L * Q * X_3 \\ W_4 &= W_4 - L * Q * X_4 \\ W_5 &= W_5 - L * Q * X_5 \\ W_6 &= W_6 - L * Q * b \end{aligned} \tag{5}$$

where W are the weights between the input signals and the neuron, L is the convergence step, Q is the local gradient, X is the input signals, b is the threshold value. The convergence step parameter is actually selected manually, for example, L= 0.1; 0.01; 0.001 and so on. It was experimentally revealed that as the convergence step decreases, the learning process of the neural network slows down. During the study, for successful further work, the optimal value of the convergence step parameter was found to be 0.1. After repeated iterations of the training process, the following result was obtained: weights before training (6):

$$W = [0.15242, -0.2142, 0.72452, 0.00121, 0.1454, 0.0214] \tag{6}$$

Weights after training (7).

$$\begin{aligned} W = [&4.81325879239291, -0.7598169807575856, 1.7113088877674243, \\ &-0.83053904119029, -1.64286055962797, -0.20327512219631635] \end{aligned} \tag{7}$$

The weights in (6) and (7) were determined by training the neural network using the backpropagation algorithm. Training involved adjusting the weights in the opposite direction to the error calculated for each input vector. To complete the learning task, we used the following tenant characteristics: tenant salary, rental price, tenant gender, tenant age, number of adults, and number of children. This data was normalized and used as input to the neural network. We carried out many iterations of training in order to minimize the error and determine the optimal values of the weights, which are reflected in (6) and (7). For full transparency, we provide in Table 1 of descriptive statistics for dataset, including key metrics:

Table 1. Descriptive statistics for the data set

Key metrics	Values
Number of observations	1,000
Average value	0.5
Median	0.5
Mode	0.5
Variance	0.0833

Substituting the obtained values of the weights, formula (8) is naturally obtained:

$$= \frac{1}{1+e^{-(4.81*X_1-0.75*X_2+1.71*X_3-0.83*X_4-1.64*X_5-0.2*b)}} \tag{8}$$

where y is the output value of the neural network, e is the exponent, X is the input signals, b is the threshold value. Passing through the neural network, formula (8) calculates the network output, which should be similar to the required value. The obtained result and the vector of input signals are shown in Table 2.

Table 2. Example of input signals to be fed to the input of a neural network

X_1	X_2	X_3	X_4	X_5	b	d	y
(500-300)/100	0	50/100	2	0	1	1	0.9999
(150-200)/100	1	30/100	2	1	1	0	0.0057

In addition to the DSS, a data mining module was created. Before launching the mining process, manual data collection was carried out from online services where users offer real estate rental services. The criteria were numerical values of rental cost and real estate area. The collected data was loaded into the mining module, where the raw data was visualized. The implementation of the module was discretely divided into two stages: the first stage included identifying and removing objects with atypical behavior, and the second stage involved calculating the optimal rental cost taking into account competitors who have similar data on the proposed property. When identifying objects with atypical behavior, the density-based spatial clustering of applications with noise (DBSCAN) machine learning method was used at the first stage of the data mining module. This algorithm is a purely algorithmic approach, not directly related to probability theory, and is based on heuristics proposed by its authors. The advantage of the chosen method is the ability to select clusters of arbitrary shape, as well as to automatically determine the number of clusters. The algorithm begins by determining the neighborhood of the object for the vector x in the metric feature space; the neighborhood is defined as the set of points located from x by no more than the value eps (9):

$$N\_eps(x)= \{y \text{ and } D|\ dist(x, y) <= eps\ \} \tag{9}$$

If $|N\_eps(x)| >= minPts$, then x is the root point, where $dist(x, y)$ is the distance function between points x and y, which is Euclidean, $N\_eps(x)$ is the set of points that are no further than than within a radius eps from point x, x is a point from the data set D, for which the neighborhood $N\_eps(x)$ is determined, y is one of the points from the data set D, which is compared with point x by distance $dist(x, y)$, eps is the neighborhood of the object, the radius parameter that determines the neighborhood of the point, $minPts$ is the minimum number of points that must be in the eps neighborhood of the point for this point to be considered a root point. This parameter is used to determine how densely packed the points should be in a cluster. The eps and $minPts$ parameters are set manually as parameters for the DBSCAN algorithm and must be greater than zero. Further, this algorithm distinguishes three types of objects: root, boundary and noise. A root object is one that contains at least $minPts$ other objects in its vicinity. The boundary is not the root but lies in the neighborhood of the root. Noise is an outlier, that is, neither root nor boundary. For all samples in the two-dimensional feature space included in the neighborhood, the procedure is repeated recurrently. Moreover, if an object does not contain a sufficient number of neighbors in its vicinity, then it is marked as boundary. This way the first cluster is selected. If unprocessed samples remain, the process is repeated from the very beginning, excluding previously processed ones in Figure 6.

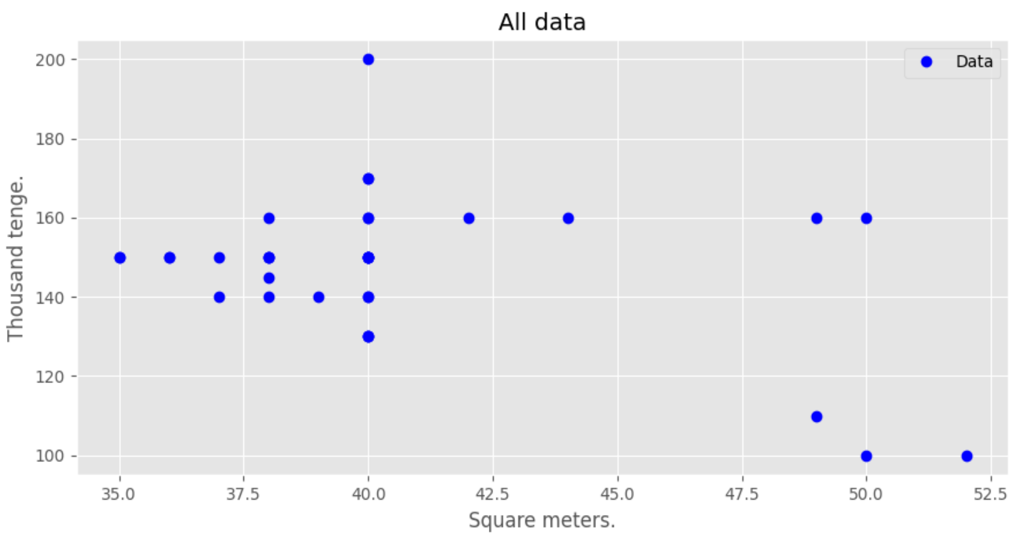

Figure 6. All data in the data analysis module

In addition, an object is randomly selected and then the formation of a new cluster begins. A recurrent search of objects occurs, and, according to the described analogy, the next cluster is selected. Upon completion of the process of enumerating all objects, the data is divided into clusters and noise patterns are detected. Noise points can be characterized as points that do not fall into any of the defined clusters in Figure 7.

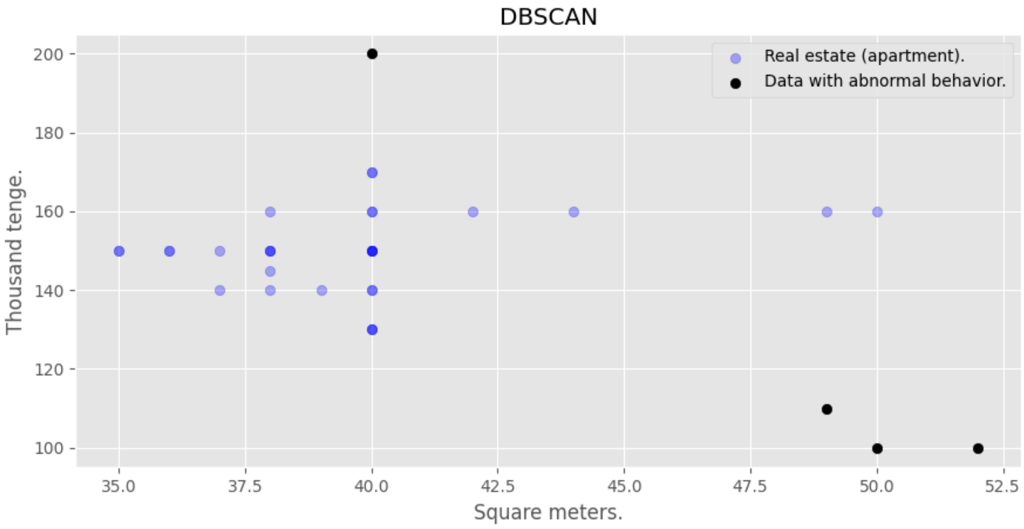

Figure 7. DBSCAN clustering in data analysis module

In DBSCAN they can be defined as points that are not root points and are not in the neighborhood of root points. May represent unexpected or exceptional data and are defined as objects with atypical behavior. But their interpretation depends on the specific task and context. In some cases, they may be seen as errors in the data, and in others as important and interesting objects. In this research work, noise objects will be defined as unnatural behavior of users in online services intended for renting out real estate. Thus, automatic detection of bots and intruders is realized. The final stage in system development is the construction of a mathematical model using the linear regression method. This system uses linear regression to predict the optimal rental price of a property based on certain criteria, such as square footage. Linear regression is applied to the cluster identified by the DBSCAN method. It is important to note that linear regression calculations do not take into account noise objects. Clustering using DBSCAN in the information system was necessary to identify objects with atypical behavior, the exclusion of which from the sample provides more accurate results in subsequent stages of data mining. After cleaning the sample from atypical objects, machine learning of linear regression is applied, where the method seeks to minimize the total amount of errors for each object, which results in a straight line with a minimum total error. As a result of the analysis, the system obtained a linear regression for a certain type of real estate in Figure 8.

By entering property data such as square footage, the numerical data is run through a linear regression formula. Consequently, the potentially optimal rental cost for the proposed property is calculated with great speed. An *.npy* file was used as data storage in the prototype information DSS in Figure 9.

This is a standard binary file for storing one arbitrary NumPy array on disk. The format stores all the necessary information about the form and type of data to correctly restore the array, even on another computer with a different architecture. That is, these are compact arrays of the same type. Python lists, on the other hand, are arrays of pointers to objects, even if they are all of the same type. Thus, specialized data structures are formed.

The primary findings of our research demonstrated the effectiveness of the prototype decision support system in real estate rental management through enhanced data handling and predictive capabilities. One pivotal piece of evidence supporting this is the implementation of density-based spatial clustering (DBSCAN) for improved data integrity, which directly contributed to more accurate predictive outputs in rental price determinations.

When compared with previous studies, our approach integrates both machine learning and traditional decision support systems to create a more robust tool tailored for the dynamic nature of the real estate rental market. A notable strength of our study is the application of linear regression in conjunction with

DBSCAN, optimizing data handling and predictive accuracy. However, a limitation is the prototype's reliance on the availability and quality of input data which can vary widely in real-world conditions. An unexpected outcome was the system's efficiency in identifying outlier data points, which significantly improved the overall reliability of the data used for machine learning processes.

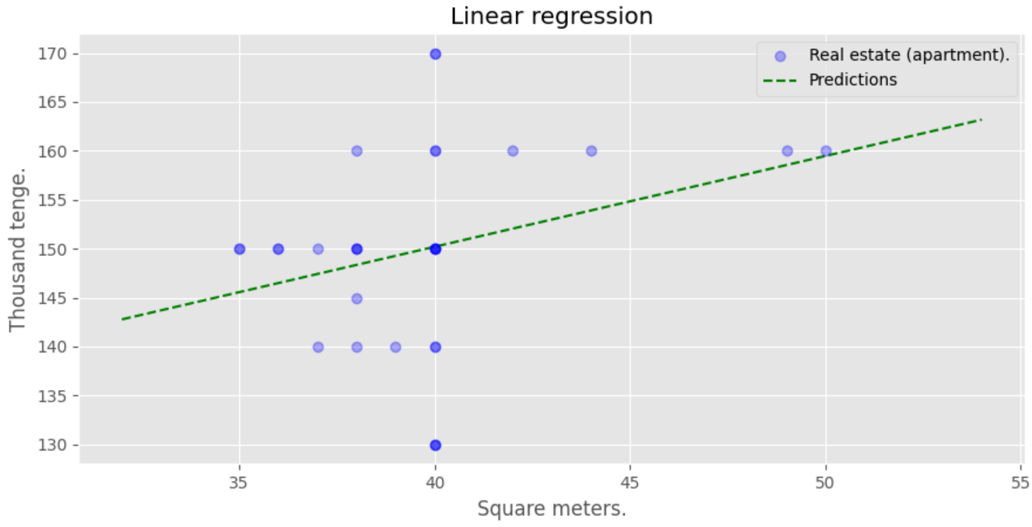

Figure 8. Linear regression in data analysis module

```
mass = np.load('C:/Users/Admin/Database1.npy')
np.save('C:/Users/Admin/Database1.npy', mass)
```

Figure 9. Execute an arbitrary request to an *.npy* file

The purpose of our study was to develop a prototype decision support system that enhances strategic decision-making for real estate rental managers through advanced data analysis tools. This research is crucial as it addresses the increasing complexity and volume of data in property management, providing a scalable solution that could be adapted to other sectors. Unanswered questions relate to the system's performance in diverse market conditions and its integration with broader types of data inputs. Future research could explore these areas, aiming to refine the system's adaptability and broaden its applicability.

4. CONCLUSION

As a result of the research work, a prototype of a decision support information system was developed for a specific company manager. The created prototype provides access to information resources and allows the end user, who does not have special knowledge in the field of information technology, to navigate between system modules and present information in the form of visualizations and reports. The core of the decision support system is the expert system module. An additional significant result is the developed data mining module, in which the DBSCAN machine learning method, a dense spatial clustering algorithm taking into account noise, was used for clustering. In the prototype, the algorithm is used to identify noise objects that represent unnatural user behavior in online services. This method can also be used to cluster data to improve sampling for a classifying neural network. In addition, a linear regression method has been applied, which is used to construct a predictive line with a minimum total error. Forecasting is performed to recommend a rental price for one of the properties the manager is considering. The obtained research results can be used in projects related to the analysis of large volumes of data and the development of decision support systems.

Our study successfully developed a prototype decision support system integrated with machine learning methods, specifically tailored for real estate rental management. This integration has significantly enhanced the system's predictive accuracy and operational efficiency, making it a valuable tool for real-time data analysis and decision-making in a dynamic market environment. Our findings underscore the importance of advanced data processing capabilities in decision support systems and suggest that integrating machine learning can effectively handle the complexities of real estate data. This research opens avenues for future exploration in the scalability and adaptability of the system across different markets and data conditions. Our conclusion not only recaps the study's achievements but also sets the stage for future inquiries into advanced decision support systems in real estate and other sectors, encouraging ongoing innovation and improvement in this vital field.

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REFERENCES

[1] Y. Liu, P. Wang, Z. He, and J. Dong, "Real estate rental market: a 10-year bibliometric-based review," *Economic Research-Ekonomska Istraživanja*, vol. 34, no. 1, pp. 1752–1788, Jan. 2021, doi: 10.1080/1331677X.2020.1848605.

[2] N. Siniak, T. Kauko, S. Shavrov, and N. Marina, "The impact of proptech on real estate industry growth," *IOP Conference Series: Materials Science and Engineering*, vol. 869, no. 6, Jun. 2020, doi: 10.1088/1757-899X/869/6/062041.

[3] D. Fields and D. Rogers, "Towards a critical housing studies research agenda on platform real estate," *Housing, Theory and Society*, vol. 38, no. 1, pp. 72–94, Jan. 2021, doi: 10.1080/14036096.2019.1670724.

[4] I. Ara, L. Turner, M. T. Harrison, M. Monjardino, P. DeVoil, and D. Rodriguez, "Application, adoption and opportunities for improving decision support systems in irrigated agriculture: a review," *Agricultural Water Management*, vol. 257, Nov. 2021, doi: 10.1016/j.agwat.2021.107161.

[5] U. T. Makhazhanova, F. A. Murzin, A. A. Mukhanova, and E. P. Abramov, "Fuzzy logic of Zadeh and decision-making in the field of loan," *Journal of theoretical and applied Information Technology*, vol. 98, no. 06, pp. 1076–1086, 2020.

[6] A. Mukhiyadin *et al.*, "Application of information technologies and methods for processing big data to the management of the educational process during the pandemic," *Journal of Theoretical and Applied Information Technology*, vol. 101, no. 2, pp. 458–470, 2023.

[7] S. Sandugash, T. Jamalbek, S. Madina, Y. Akbota, and A. Ainur, "Building a standard model of an information system for working with documents on scientific and educational activities," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 9, 2021.

[8] J. Tussupov *et al.*, "Analysis of formal concepts for verification of pests and diseases of crops using machine learning methods," *IEEE Access*, vol. 12, pp. 19902–19910, 2024, doi: 10.1109/ACCESS.2024.3361046.

[9] A. S. Lepley, G. E. Norte, and M. Ferlic, "Chapter 75 - Data management: how to manage data safely and effectively in an organized manner," in *Translational Sports Medicine*, Elsevier, 2023, pp. 377–382.

[10] S. C. K. Tekouabou, Ş. C. Gherghina, E. D. Kameni, Y. Filali, and K. I. Gartoumi, "AI-based on machine learning methods for urban real estate prediction: a systematic survey," *Archives of Computational Methods in Engineering*, vol. 31, no. 2, pp. 1079–1095, Mar. 2024, doi: 10.1007/s11831-023-10010-5.

[11] H. Rabiei-Dastjerdi, G. McArdle, S. A. Matthews, and P. Keenan, "Gap analysis in decision support systems for real-estate in the era of the digital earth," *International Journal of Digital Earth*, vol. 14, no. 1, pp. 121–138, Jan. 2021, doi: 10.1080/17538947.2020.1808719.

[12] F. Ullah and S. M. E. Sepasgozar, "Key factors influencing purchase or rent decisions in smart real estate investments: A system dynamics approach using online forum thread data," *Sustainability*, vol. 12, no. 11, May 2020, doi: 10.3390/su12114382.

[13] M. Alloghani, D. Al-Jumeily, J. Mustafina, A. Hussain, and A. J. Aljaaf, "A systematic review on supervised and unsupervised machine learning algorithms for data science," in *Supervised and unsupervised learning for data science*, 2020, pp. 3–21.

[14] I. H. Sarker, A. S. M. Kayes, S. Badsha, H. Alqahtani, P. Watters, and A. Ng, "Cybersecurity data science: an overview from machine learning perspective," *Journal of Big Data*, vol. 7, no. 1, Dec. 2020, doi: 10.1186/s40537-020-00318-5.

[15] S. N. Alsubari, "Data analytics for the identification of fake reviews using supervised learning," *Computers, Materials & Continua*, vol. 70, no. 2, pp. 3189–3204, 2022, doi: 10.32604/cmc.2022.019625.

[16] J. Tussupov *et al.*, "Applying machine learning to improve a texture type image," *Eastern-European Journal of Enterprise Technologies*, vol. 2, no. 2 (122), pp. 13–18, Apr. 2023, doi: 10.15587/1729-4061.2023.275984.

[17] A. Naizagarayeva *et al.*, "Detection of heart pathology using deep learning methods," *International Journal of Electrical and Computer Engineering*, vol. 13, no. 6, pp. 6673–6680, Dec. 2023, doi: 10.11591/ijece.v13i6.pp6673-6680.

[18] G. Taubayev *et al.*, "Machine learning algorithms and classification of textures," *Journal of Theoretical and Applied Information Technology*, vol. 98, no. 23, pp. 3854–3866, 2020.

[19] J. G. Sánchez-Torija, M. A. F. Nieto, and P. J. G. Serrano, "Energy solvency. A new concept to prevent energy poverty in Spain," *Energy Efficiency*, vol. 15, no. 8, Dec. 2022, doi: 10.1007/s12053-022-10070-9.

[20] G. Lăzăroiu, O. Neguriţă, I. Grecu, G. Grecu, and P. C. Mitran, "Consumers' decision-making process on social commerce platforms: online trust, perceived risk, and purchase intentions," *Frontiers in Psychology*, vol. 11, May 2020, doi: 10.3389/fpsyg.2020.00890.

[21] J. W. Burton, M. Stein, and T. B. Jensen, "A systematic review of algorithm aversion in augmented decision making," *Journal of Behavioral Decision Making*, vol. 33, no. 2, pp. 220–239, Apr. 2020, doi: 10.1002/bdm.2155.

[22] A. S. Yalcin, H. S. Kilic, and D. Delen, "The use of multi-criteria decision-making methods in business analytics: a comprehensive literature review," *Technological Forecasting and Social Change*, vol. 174, Jan. 2022, doi: 10.1016/j.techfore.2021.121193.

[23] C. J. Fusch, "Risk management strategies for sustainable rental real estate profitability," Walden University, 2019.

[24] H. M. S. N. Samarasekara, M. B. Purushothaman, and F. E. Rotimi, "Interrelations of the factors influencing the whole-life cost estimation of buildings: a systematic literature review," *Buildings*, vol. 14, no. 3, Mar. 2024, doi: 10.3390/buildings14030740.

[25] A. S. C. Pires, F. A. F. Ferreira, M. S. Jalali, and H.-C. Chang, "Barriers to real estate investments for residential rental purposes: mapping out the problem," *International Journal of Strategic Property Management*, vol. 22, no. 3, pp. 168–178, May 2018, doi: 10.3846/ijspm.2018.1541.

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