https://doi.org/10.31891/csit-2024-4-9
UDC 004.6:004.65:004.89

Vitaliy KOBETS, Konstantin FEDCHENKO
Kherson State University

WEB SERVICE MANAGEMENT SYSTEM FOR PREDICTING REAL ESTATE PRICES USING MACHINE LEARNING TECHNIQUES

Today there are many different web services for renting real estate, but none of them provides price forecasting capabilities. There is a need to create a platform that allows users to receive accurate real estate price forecasts with minimal time expenditures. The aim of this paper is to develop the architecture of a web service for real estate price forecasting, considering various apartment characteristics. We have prepared a review and analysis of existing analogues of real estate rental web services, functional and non-functional requirements for a web service for apartment price forecasting. The high-level architecture and technical tasks for the participants of our web service were also developed and described in our research.

The paper proposes the development of a web service that predicts real estate prices based on various property characteristics. The key objectives are: analyze existing real estate rental web services and identify functional gaps, particularly the lack of price prediction capabilities; establish technical requirements for a comprehensive web service that unifies tenants, landlords, and administrators to facilitate informed decision-making; utilize machine learning techniques, such as linear regression, random forest, and decision trees, to develop a price forecasting module within the web service; evaluate the performance of different machine learning models using RMSE metric.

The paper presents the high-level architecture of the web service, including modules for user registration, data validation, apartment search and interaction, and price forecasting. The experimental results demonstrate that the random forest model outperforms linear regression and decision trees in predicting apartment rental prices in Kyiv. Overall, the study highlights the potential of integrating machine learning into real estate web services to enhance transparency and informed decision-making for both tenants and landlords.

Keywords: real estate, price forecasting web service, apartment characteristics, price prediction, machine learning.

Віталій КОБЕЦЬ, Костянтин ФЕДЧЕНКО
Херсонський державний університет

СИСТЕМА УПРАВЛІННЯ ВЕБСЕРВІСОМ ДЛЯ ПРОГНОЗУВАННЯ ЦІН НЕРУХОМОСТІ З ВИКОРИСТАННЯМ МЕТОДІВ МАШИННОГО НАВЧАННЯ

Сьогодні існує багато різних веб-сервісів для оренди нерухомості, але жоден з них не надає можливості прогнозування цін. Існує потреба у створенні платформи, яка дозволить користувачам отримувати точні прогнози цін на нерухомість з мінімальними часовими витратами. Метою цієї статті є розробка архітектури веб-сервісу для прогнозування цін на нерухомість з урахуванням різних характеристик квартир. Ми підготували огляд та аналіз існуючих аналогів веб-сервісів оренди нерухомості, функціональні та нефункціональні вимоги до веб-сервісу для прогнозування цін на квартири. Також було розроблено та описано високорівневу архітектуру та технічні завдання для учасників нашого веб-сервісу.

У статті пропонується розробка веб-сервісу, який прогнозує ціни на нерухомість на основі різних характеристик нерухомості. Основними завданнями є: аналіз існуючих веб-сервісів оренди нерухомості та виявлення функціональних прогалин, зокрема, відсутність можливості прогнозування цін; встановлення технічних вимог до комплексного вебсервісу, який об'єднує орендарів, орендодавців та адміністраторів для полегшення прийняття обґрунтованих рішень; використання методів машинного навчання, таких як лінійна регресія, випадковий ліс та дерева рішень, для розробки модуля прогнозування цін в рамках веб-сервісу; оцінка продуктивності різних моделей машинного навчання за допомогою метрики RMSE.

У статті представлено високорівневу архітектуру веб-сервісу, що включає модулі для реєстрації користувачів, валідації даних, пошуку та взаємодії з квартирами, а також прогнозування цін. Експериментальні результати демонструють, що модель випадкового лісу перевершує лінійну регресію та дерева рішень у прогнозуванні цін на оренду квартир у Києві. Загалом, дослідження підкреслює потенціал інтеграції машинного навчання у веб-сервіси нерухомості для підвищення прозорості та прийняття обґрунтованих рішень як для орендарів, так і для орендодавців.

Ключові слова: нерухомість, вебсервіс прогнозування цін, характеристики квартир, прогнозування цін, машинне навчання.

Introduction

The informatization of society, aimed at facilitating the resolution of important and current applied problems both globally and in specific areas of activity, helps simplify the process of learning and adapting to new demands of the times, saving time—the most scarce resource—for alternative opportunities.

With the advancement of technology, accelerated migration processes, and urban growth, there is a need for accurate real estate price forecasting. Many rental services do not offer price prediction capabilities, which is crucial for landlords and tenants looking to minimize risks and optimize their limited resources. Therefore, our project focuses on creating a web service that predicts real estate prices based on the analysis of various apartment characteristics.

Today, there are many web services for real estate rentals, but none offer real estate price prediction. This is a significant drawback since forecasting real estate prices allows users to make decisions that are more informed. Our web service provides a solution to this problem by offering accurate price predictions based on an analysis of factors such as the number of rooms, floor, total area, pet-friendliness, neighborhood, wall material, and proximity to the metro.

The **purpose** of this paper is to develop the architecture of a web service for predicting real estate prices that considers various apartment characteristics and provides accurate price forecasts. Currently, there are no analogs of our web-based management system for real estate price prediction that take into account a wide range of apartment parameters.

This paper is structured as follows. Section 2 provides a literature review on web service management systems for real estate rentals; Section 3 explores the requirements for a real estate price forecasting web service; Section 4 includes a review and analysis of existing analogs of real estate rental web services; Section 5 contains the web service architecture; and the final section presents the conclusions.

Related works

The paper [1] discusses the use of machine learning, specifically neural networks, in house price analysis in Poznań, Poland in 2018 and 2019 compared to traditional multiple regression models. Multiple regression models are commonly used in real estate appraisal, but have limitations with nonlinear data and large datasets. Neural networks can handle nonlinear relationships and large amounts of data well. The study compared a multiple regression model to a multilayer perceptron (MLP) neural network for predicting house prices. Both models tended to overestimate prices when tested on a control sample from 2019. The neural network performed slightly better but still had accuracy issues, likely due to sample size limitations. However, more research is needed to improve accuracy, especially with larger training datasets. The paper concludes that while neural networks show promise for real estate valuation, traditional regression methods still have value. The integration of machine learning into property appraisal practice could help move the industry towards more automated, data-driven approaches.

The application of statistical models and machine learning in real estate valuation has been a topic of growing interest among researchers and practitioners. Traditional multiple regression models have been widely used in real estate appraisal since the 1970s, especially for mass valuation purposes [2]. However, these models have limitations, particularly when dealing with nonlinear relationships and large datasets [3, 4].

The hedonic regression method, which uses property features as explanatory variables, has been a popular approach for analyzing house prices [5, 6]. Fleming and Nellis [7] described a linear hedonic regression model for determining house price indices. However, as Gibbons and Machin [8] noted, traditional hedonic approaches using cross-sectional data may not adequately address potential endogeneity issues.

Spatial autocorrelation in real estate markets has been recognized as an important factor, leading to the development of spatial regression models [9, 10]. Anselin [10] and Páez and Scott [11] have discussed various spatial econometric techniques for urban analysis. Bourassa et al. [12] compared different methods for predicting house prices with spatial dependence.

In recent years, machine learning techniques, particularly neural networks, have gained attention in real estate valuation [13, 14]. Peterson and Flanagan [13] explored neural network hedonic pricing models in mass real estate appraisal, while Curry et al. [14] compared neural networks with non-linear statistical methods in modeling price-quality relationships.

The integration of machine learning into property appraisal practice is seen as a potential shift from manual to electronic work in the industry [15]. Wu et al. [16] highlighted the power of machine learning in dealing with big data challenges in urban housing price analysis. However, some researchers emphasize the continued relevance of traditional methods alongside machine learning approaches [17]. Lulin and Li [17] found that machine learning models can significantly improve accuracy compared to linear multiple regression and spatial econometric models, but also noted the value of combining different approaches.

The paper [18] explores various machine learning techniques for predicting housing prices, using a dataset of housing prices in Beijing. The main methods examined are: Random Forest, Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Hybrid Regression (combining multiple models), Stacked Generalization Regression. The authors preprocessed and analyzed the dataset, which contained over 300,000 entries with 26 variables [18]. They then applied the different machine learning models and compared their performance using the Root Mean Squared Logarithmic Error (RMSLE) metric.

They reveal that Random Forest performed best on the training set but was prone to overfitting, XGBoost and LightGBM showed good accuracy and faster performance, Hybrid Regression and Stacked Generalization showed promising results, with Stacked Generalization performing best on the test set. All methods have different trade-offs in terms of accuracy, overfitting risk, and computational complexity. The authors suggest further research into combining different models and exploring the factors behind the good performance of tree-based models.

Housing price prediction has been a topic of significant interest in recent years, with researchers exploring various machine learning techniques to improve accuracy. Traditional approaches often relied on the House Price Index (HPI) to estimate changes in housing prices [19]. However, as housing prices are influenced by multiple factors such as location, area, and population, more sophisticated methods are required for individual housing price prediction.

Several studies have demonstrated the potential of machine learning approaches in housing price prediction. Fan et al. compared different machine learning algorithms for house price prediction, showing the capability of these methods to improve accuracy [20]. Similarly, Phan conducted a study on housing price prediction in Melbourne, Australia, using machine learning algorithms [21]. Mu et al. also explored various machine learning methods for housing value forecasting [22].

While these studies established the effectiveness of traditional machine learning approaches, they often focused on comparing individual model performance without considering the potential of combining different models. Lu et al. addressed this gap by conducting an experiment using a hybrid regression technique for forecasting house prices, which required intensive parameter tuning to find the optimal solution [23].

The current study builds upon this existing research by not only comparing traditional machine learning methods such as Random Forest, XGBoost, and LightGBM but also exploring advanced techniques like Hybrid Regression and Stacked Generalization. This approach allows for a comprehensive evaluation of both individual model performance and the potential benefits of model combination in housing price prediction. By comparing the performance of different models using the Root Mean Squared Logarithmic Error (RMSLE) metric, the research provides insights into the strengths and weaknesses of each approach.

The authors [24] propose novel hybrid models for improved house price prediction of Hybrid Bayesian Optimization (HBO) models combined with Stacking (HBOS), Bagging (HBOB), and Transformer (HBOT) techniques. The paper emphasizes the importance of accurate predictions for economic stability and policy-making, presenting innovative models and robust evaluation methods to address the complexities of the real estate market.

The literature suggests a growing trend towards incorporating machine learning techniques in real estate valuation, while also recognizing the ongoing utility of traditional statistical methods. Further research is needed to refine these approaches and determine their optimal applications in various real estate market contexts.

Methodology of research

During the process of forming final ideas and tasks for the future web resource, it was decided to investigate several resources that provide real estate rental services. Prior to studying these resources, we established 12 criteria that define the quality and level of services related to real estate rental on respective web services in Ukraine in Table 1, where PS denotes paid service.

Table 1

Analysis of Functionality of Real Estate Rental Service Analogs

Criteria	lun.ua	dom.ria.com	flatfy.ua	rieltor.ua	olx.ua	24realty.ua	100realty.ua
1. Price Prediction Capability	no	no	no	no	no	no	no
2.Ability to Publish Own Listings	yes	yes	yes	yes	yes	yes	yes
3. Information Filtering by Parameters	yes	yes	yes	yes	yes	yes	yes
4.Section for Social Housing	no	no	no	no	no	no	no
5. Landlord Ratings	no	yes	no	no	no	no	no
6. Property Verification	yes	yes	yes	yes	no	no	no
7. Landlord Verification	yes	yes	yes	yes	no	no	no
8. User Reviews	yes	yes	yes	yes	yes	no	no
9.Integration with Maps	yes	yes	yes	yes	yes	yes	no
10.Mobile App Support	yes	yes	yes	yes	yes	no	no
11. Ability to Select Priority Listings	yes	yes	no	no	yes	no	no
12. Cost of Services	PS	PS	free	PS	free	PS	PS

We investigated the 7 most popular services in the Ukrainian market: lun.ua, dom.ria, flatfy.ua, rieltor.ua, olx.ua, 24realty.ua, 100realty.ua. Key criteria for our evaluation were the ability to forecast prices and property verification. The study revealed that none of the resources have the function of predicting rental property prices.

Almost all websites support the function of posting personal listings, and all of them support information filtering by necessary parameters. During the research, it was found that none of the resources provide a search function specifically for socially subsidized housing, and almost all sites overlook the possibility of creating a landlord rating. Companies, in turn, have practically no ability to verify the existence of tenants listed on their site.

The selection of these parameters was guided by their ability to address the core needs of users and ensure a robust, transparent, and user-friendly platform. The **price prediction capability** was prioritized as it enables users to make informed decisions by providing accurate market data analysis. This feature minimizes risks for both landlords and tenants by ensuring appropriate pricing when renting or buying. The **ability to publish own listings** was included to open up the platform to a wider audience, lowering the barriers to entry for individuals and increasing the database of available properties.

To enhance usability, **information filtering by parameters** allows users to efficiently search for properties based on criteria such as price, location, and number of rooms. This significantly improves the user experience by saving time and effort. In addition, the introduction of a **section for social housing** ensures that less privileged populations have access to affordable housing options, demonstrating the platform's commitment to social responsibility while broadening its audience.

Landlord ratings and **user reviews** have been incorporated to build a community of trust and transparency. Ratings help tenants make informed decisions based on the experiences of others, while reviews motivate landlords to improve their services. Similarly, **property verification** and **landlord verification** plays a crucial role in fraud prevention, ensuring that users can trust the information provided on the platform.

The integration of advanced tools such as **map functionality** enhances the search experience by allowing users to quickly assess a property’s location and proximity to key infrastructure. Additionally, **mobile app support** makes the platform accessible anytime and anywhere, meeting modern user expectations and expanding the potential user base. Features such as the **ability to select priority listings** add value by allowing users to increase the visibility of their properties while creating monetization opportunities for the platform. Finally, providing a clear and transparent presentation of the **cost of services** ensures that users can effectively plan their budgets, thereby fostering trust and loyalty.

Together, these parameters contribute to the usability, transparency and attractiveness of the platform, ensuring that it meets the diverse needs of users while remaining competitive in the market.

This analysis of analogs among the most well-known rental property search websites helped identify functional capabilities, strengths, weaknesses, and test the novelty of the idea of price forecasting. We see the feasibility of creating a comprehensive platform to unite market agents such as:

● Tenants interested in improving and expediting their housing search and rental process.

● Owners and real estate agents need to rent out properties.

In our opinion, close cooperation among the mentioned parties will help clearly define the target audience, highlighting the advantages of the web service system for both tenants and landlords (Table 2), as well as the advantages for newcomers and service owners (Table 3).

Table 2

Advantages of the web service system for rental properties for tenants and landlords

For potential tenants	For landlords
Ability to get accurate price forecasts for rented properties.	Increased number of applications due to informed tenants.
Access to verified information about landlords and properties.	Building trust in their profile through verification and rating systems.
Convenient use of filters to search for properties based on criteria.	Ability to analyze the market and adjust rental rates based on forecasts.
Access to interactive maps for easy property selection by location.	Enhanced competitiveness through improved service quality and transparency.
Ability to view reviews and ratings from other tenants.	

Table 3

Advantages of the web service system for rental properties for tenants and service owners

For newcomers (tenants)	For service owners
Increased trust in the service due to a transparent verification and rating system.	Attraction of new users through improved service quality and functionality.
Easy finding of properties that meet their needs.	Opportunity to expand the service through new features such as price forecasting and interactive maps.
Enhanced usability of the service through integration with other useful tools (e.g., maps, transportation).	Commercialization and monetization of the service through the implementation of paid features and subscriptions.

Accordingly, we have formulated a technical specification that includes information about the required functionality of the future web service (Table 4).

Three main user groups have been identified. The first group consists of potential tenants who can create their profiles, add and verify information about themselves, track available rental offers in the housing market, and find those that best meet their needs. The second group includes landlords who want to get in touch with potential tenants, monitor the rental market conditions in a specific segment, and have the ability to promote their real estate properties and rental programs. The third group comprises administrators responsible for verifying information, confirming data, and having certain levers to address unethical actions from tenant and landlord profiles. Functional requirements for the first and second groups are defined in Table 4. The functionality for administrators is outlined below:

Functional Requirements for the Rental Housing Service Administrators:

● Authenticate and register users in the system.

● Verify and validate information from tenants and landlords (e.g., confirming certificates, documents from publicly accessible registries).

● Block and delete landlord and tenant profiles in case of unethical actions or violations of service rules.

● Monitor compliance of listings and profiles with service rules.

● Manage and moderate content (listings, reviews, ratings) to ensure service quality and reliability.

Thus, the system ensures transparency and reliability in interactions among tenants, landlords, and administrators, promoting service quality and user satisfaction.

Table 4

Functional Requirements for the Housing Rental Service

For the tenant	For the landlord
Authenticate and register as a user in the system.	Authenticate and register as a user in the system.
Create/Edit/Delete their own profile (phone number, email, photo, description).	Access tenant contacts based on mutual interest.
Add and verify preferences and needs (type of property, location, number of rooms, etc.).	Create/Edit/Delete their own profile.
Search and track rental offers that match specified criteria.	Create/Edit/Hide/Close property profiles (photos, descriptions, parameters).
View detailed descriptions of apartments based on their characteristics.	Verify property data to enhance trust from tenants.
Access landlord contacts upon mutual interest.	Predict the price of the apartment based on its characteristics.
View landlord profiles.	Track applications from potential tenants.
Send requests to view/rent apartments.	View tenant profiles and their ratings.
Predict the price of an apartment based on its characteristics.	Leave reviews about tenants and view their reviews about rental properties.
View ratings and reviews of landlords.	
Leave reviews and rate rented properties and landlords.	

Results

For a detailed description of the overall functional system at the conceptual level, we utilized an activity diagram (Fig. 1). It shows external entities (actors) interacting with and using the functionality of the system, representing all user groups of the service. The activity diagram organizes the functional flow vertically and compactly, showing each functional block side by side.

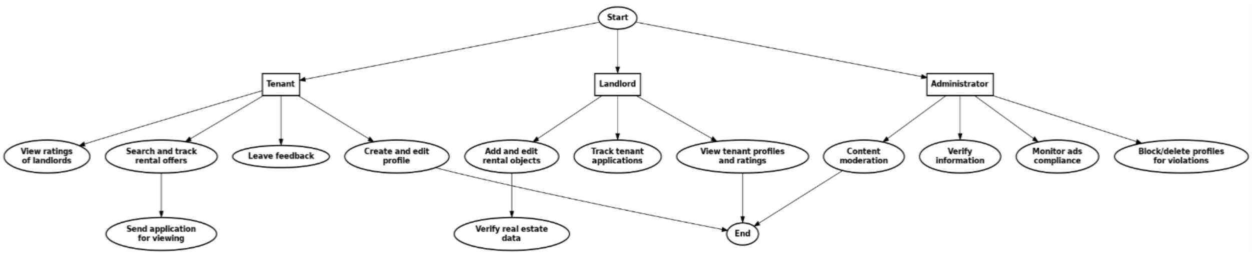

Fig. 1. Activity Diagram of Property Price Forecasting Web Service Functions

The activity diagram provides a more structured and visually clear representation of the interactions between user groups (agents) and system functions. It effectively replaces the use case diagram by showing the sequence of actions performed by each group. The high-level architecture of the future web service illustrates the connections between these modules. System decomposition helped identify 11 functional modules, some of which are versatile and serve multiple agent groups (Fig. 2).

The registration and authentication modules are responsible for creating user accounts in the system and managing user logins, respectively. The data validation module includes the main function of checking users and administrators, incorporating a mechanism for manually verifying registered users. The tenant and landlord (proprietor) modules handle the functional capabilities of their respective dashboards and have easy access to other user profile-related modules.

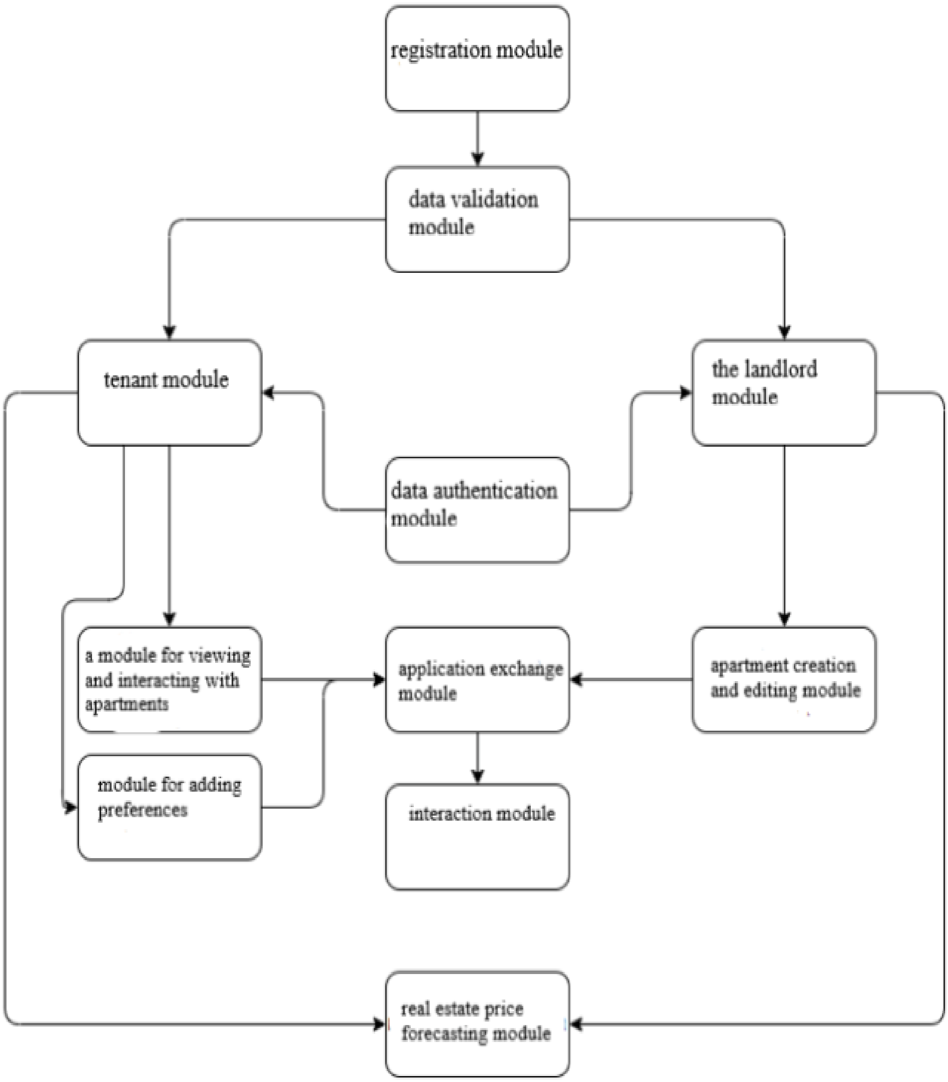

Fig. 2. High-Level Architecture of Property Price Forecasting Web Service

The apartment viewing and interaction module allows tenants to explore the real estate market, search for apartments based on specific criteria, view property details, and mark them as favorites. The preferences module enables applicants to add information about their preferences when selecting an apartment. The apartment creation and editing module allows landlords to create profiles for their apartments based on their characteristics and owner requirements, as well as interact with profiles by editing or closing them to be viewed by other agents.

The application exchange module enables tenants and landlords to clearly propose themselves as tenants/owners respectively, expressing interest in real estate objects. It also includes functionality for submitting and processing applications within the system. The interaction module removes profile privacy between users, revealing full contact information of each potential agreement participant for further communication and cooperation outside the service based on mutual consent. The web service provides participants the ability to reject applicants who do not meet their rental requirements.

The property price forecasting module calculates the average rental price (with confidence intervals) based on specified characteristics, identifying overpricing or underpricing for similar housing offers and aiding in detecting potential fraudulent transactions or rentals under force majeure conditions. If the price of some apartments significantly exceeds similar offers from other landlords, uniqueness confirmation of the offer based on specific apartment characteristics not found in other real estate is required.

Experimental model

Using the Real estate price forecasting module, one can select a machine learning model that provides the best quality of apartment rental price forecast using the RMSE criterion (for both forecasting and classification models). To predict the price of renting an apartment depending on the predictors, we can consider the use of linear multiple regression, random forest, decision tree methods. To do this, it is necessary to consider the dependent variable (rental price per month) and 10 independent variables (predictors) using dataset of 2040 samples of Kyiv (Ukraine):

price - the price of an apartment in $1000
totsp - total area of the apartment, sq.m.
livesp - living area of the apartment, sq.m.
kitsp - kitchen area, sq.m.
dist - distance from the apartment to the city centre in km.
metrdist - distance to the metro station in minutes
walk: 1 - on foot from the metro, 0 - by transport
brick: 1 - brick building, 0 - other building
floor: 1 - floor other than the first and last, 0 - first or last floor.
code - city districts from 1 to 8

The correlation between the variables is as follows (Fig. 3):

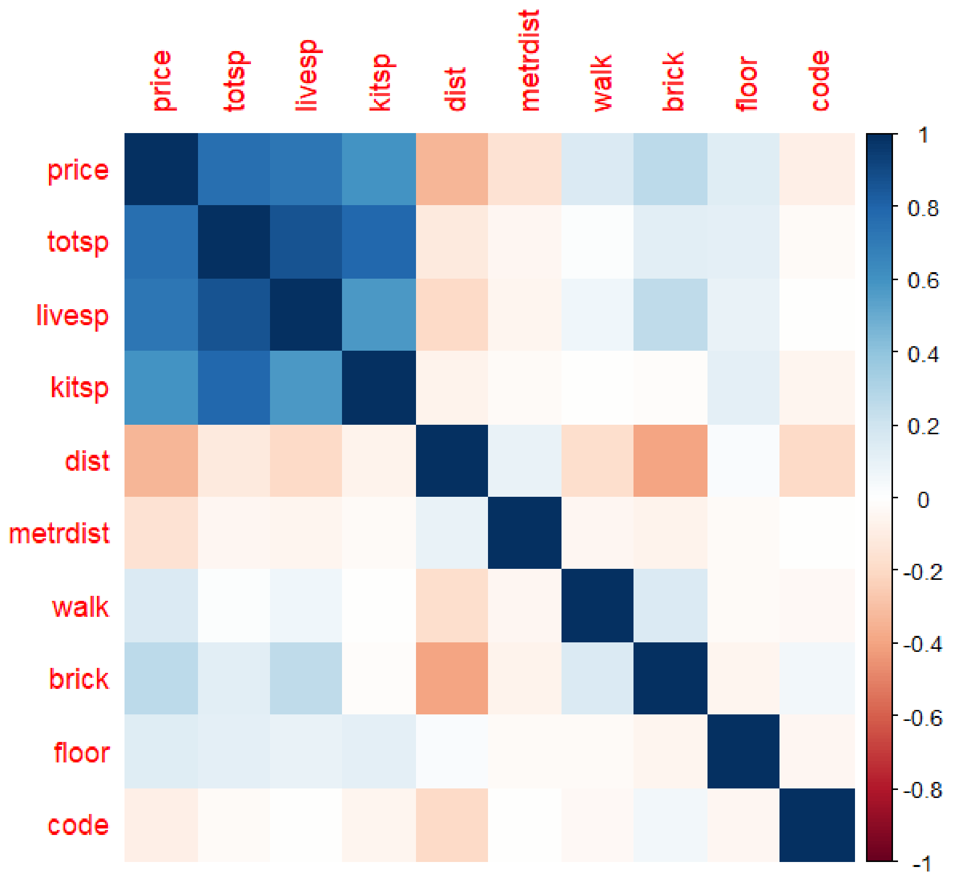

Fig. 3. Correlation between variables (blue color corresponds to a positive correlation, red color corresponds to a negative correlation)

The histogram for the price of renting an apartment in Kyiv is shown in Fig. 4 (n=2040 rental offers).

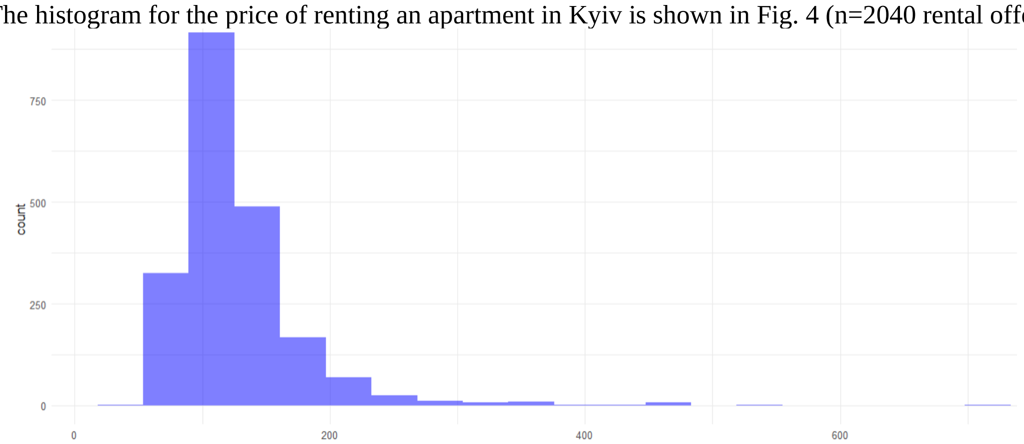

Fig. 4. Histogram of apartment rental prices in Kyiv

The calculation of VIF for the predictors shows that there is no multicollinearity (VIF<10), i.e. all the predictors can be used to predict the price of renting an apartment (Fig. 5):

```
   totsp   livesp    kitsp     dist metrdist     walk    brick    floor 
7.738744 4.922180 2.851522 1.268720 1.016622 1.056505 1.297474 1.023024 
    code 
1.041753 
```

Fig. 5. VIF coefficients for predictors of apartment rental prices

The results of the linear regression show that all the predictors have a statistically significant impact on the rental price of an apartment (Fig. 6):

```
lm(formula = price ~ ., data = train)

Residuals:
    Min      1Q  Median      3Q     Max 
-110.10  -14.88   -0.70   10.66  410.51 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -26.9336     6.7600  -3.984 7.11e-05 ***
totsp         1.8086     0.1416  12.772  < 2e-16 ***
livesp        1.1661     0.2134   5.463 5.52e-08 ***
kitsp         1.2010     0.4775   2.515 0.012006 *  
dist         -3.1897     0.2631 -12.125  < 2e-16 ***
metrdist     -1.3464     0.2081  -6.470 1.34e-10 ***
walk         10.0979     1.7394   5.805 7.90e-09 ***
brick         8.6527     1.9443   4.450 9.24e-06 ***
floor         6.8975     1.9744   3.493 0.000491 ***
code         -2.5899     0.3668  -7.061 2.58e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 30.03 on 1424 degrees of freedom
Multiple R-squared:  0.6976,	Adjusted R-squared:  0.6957 
F-statistic: 365.1 on 9 and 1424 DF,  p-value: < 2.2e-16
```

Fig. 6. Linear regression model for predicting the price of an apartment

At the same time, the predictors totsp, livesp, kitsp, walk, brick, floor have a direct impact on the rental price of an apartment, while the predictors dist, metrdist, code have a negative impact on the rental price of an apartment.

When applying the Random forest method, the most important factors of influence are the total and living space of the rented apartment, the kitchen area and the distance from the apartment to the city center (Fig. 7).

```
            %IncMSE
totsp    1855.58661
livesp    816.92381
kitsp     515.73011
dist      402.23938
metrdist   51.80257
walk       63.21499
brick      78.14269
floor      16.17641
code      147.56076
```

Fig. 7. The importance of Random forest model predictors

The decision tree method distributes apartments according to the most important predictors (total and living space, distance from the apartment to the city center) (Fig. 8).

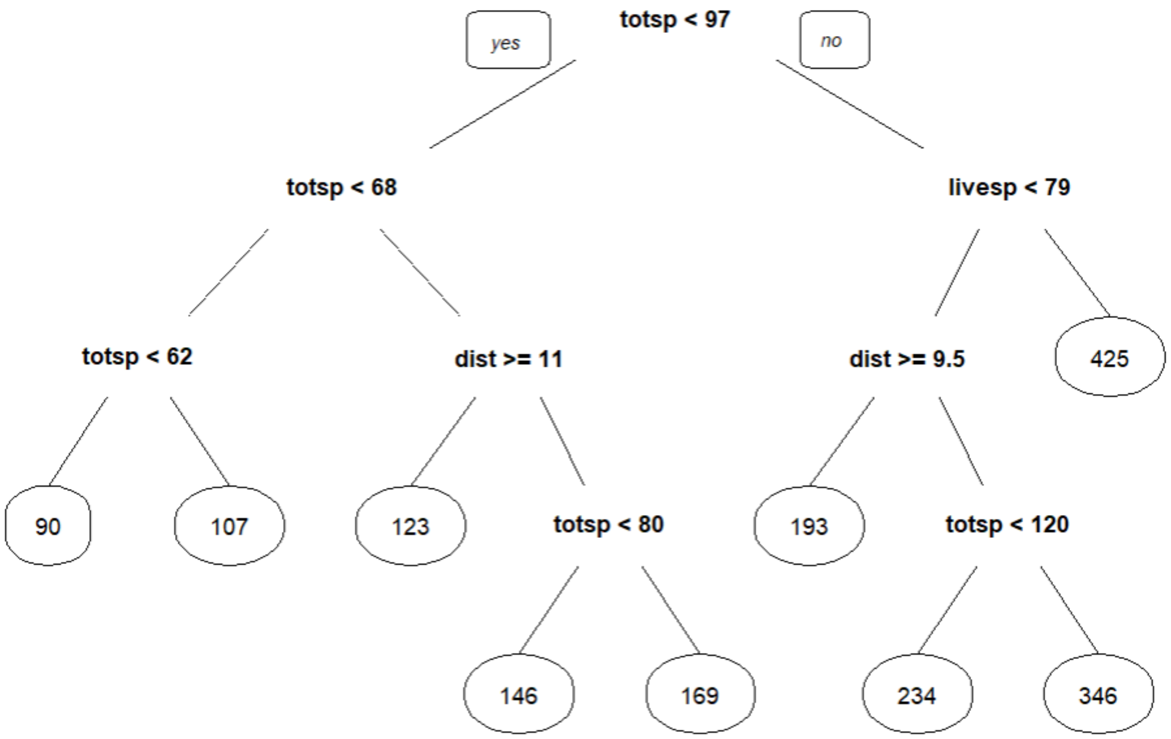

Fig. 8. Distribution of apartments by the most important predictors of the Decision Trees model

After comparing the quality of the forecast for the rental price of an apartment, the following results were obtained (Table 5).

Table 5

RMSE of machine learning methods

Methods	Linear regression	Random Forest	Decision Trees
RMSE	27.68	23.56	73.82

Based on the results of applying the Real estate price forecasting module, it was found that the best forecast for the price of renting an apartment in Kyiv according to the RMSE criterion and for the identified predictors is provided by the Random Forest method.

Conclusions

The architecture of the real estate rental web service with property price forecasting has been developed. Currently, there is no analogue of our web service for housing search that combines apartment search and price forecasting. Technical specifications have been developed for tenants, landlords, and administrators, outlining their roles. An overview and analysis of existing analogs of property listing web services have been conducted, functional and non-functional requirements have been developed, and a high-level architecture of the apartment rental web service has been described. Additionally, an analysis of price forecasting using the R software package has been conducted. The best result for predicting the rental price of an apartment in Kyiv was provided by the random forest method.

Our future work will focus on developing the back-end and front-end parts of the property rental web service and adding a module to the web service using machine learning tools based on various algorithms. The next step will be testing, adapting, and refining this system for potential users.

References

1. Foryś, I. (2022). Machine learning in house price analysis: regression models versus neural networks. *Procedia Computer Science*, 207, 435–445. https://doi.org/10.1016/j.procs.2022.09.078
2. Robey, S. L., McKnight, M. A., Price, M. R., & Coleman, R. N. (2019). Considerations for a Regression-Based Real Estate Valuation and Appraisal Model: A Pilot Study. *Accounting and Finance Research*, 8(2), 99. https://doi.org/10.5430/afr.v8n2p99
3. Kobets, V., Weissblut, A. Nonlinear Dynamic model of a microeconomic system with different reciprocity and expectations types of firms: Stability and bifurcations (2016) *CEUR Workshop Proceedings*, 1614, pp. 502-517. https://ceur-ws.org/Vol-1614/paper_90.pdf
4. Zhang, Q. (2021). Housing Price Prediction Based on Multiple Linear Regression. *Scientific Programming*, 2021, 1–9. https://doi.org/10.1155/2021/7678931
5. Zubrii, M., Mazur, A., & Kobets, V. (2018). Forecasting Real Option Price Model by Means of Evolutionary and Genetic Algorithms. In *Lecture notes in mechanical engineering* (pp. 214–224). https://doi.org/10.1007/978-3-319-93587-4_23

6. Foryś, I. (2022). Machine learning in house price analysis: regression models versus neural networks. *Procedia Computer Science*, 207, 435–445. https://doi.org/10.1016/j.procs.2022.09.078
7. Sopranzetti, B.J. (2015). Hedonic Regression Models. In: Lee, CF., Lee, J. (eds) *Handbook of Financial Econometrics and Statistics*. Springer, New York, NY. https://doi.org/10.1007/978-1-4614-7750-1_78
8. Banzhaf, H. S. (2021). Difference-in-Differences Hedonics. *Journal of Political Economy*, 129(8), 2385–2414. https://doi.org/10.1086/714442
9. Wilhelmsson, M. (2022). Spatial Model in Real Estate Economics. *Housing Theory and Society*, 9(2), 92–101. https://doi.org/10.1080/140360902760385646
10. Tang, Z., Zhang, Z., Zuo, L., Wang, X., Hu, S., & Zhu, Z. (2020). Spatial Econometric Analysis of the Relationship between Urban Land and Regional Economic Development in the Beijing–Tianjin–Hebei Coordinated Development Region. *Sustainability*, 12(20), 8451. https://doi.org/10.3390/su12208451
11. Furková, A. (2024). Spatial patterns of European innovation: a spatial econometric approach with technological proximity weights. *Review of Applied Socio-Economic Research*, 27(1), 5–17. https://doi.org/10.54609/reaser.v27i1.291
12. Geerts, M., Vanden Broucke, S., & De Weerdt, J. (2023). A Survey of Methods and Input Data Types for House Price Prediction. *ISPRS International Journal of Geo-Information*, 12(5), 200. https://doi.org/10.3390/ijgi12050200
13. Nyanda, F., Muyingo, H., & Wilhelmsson, M. (2024). Machine Learning Valuation in Dual Market Dynamics: A Case Study of the Formal and Informal Real Estate Market in Dar es Salaam. *Buildings*, 14(10), 3172. https://doi.org/10.3390/buildings14103172
14. Curry, B., Morgan, P., & Silver, M. (2022). Neural networks and non-linear statistical methods: an application to the modelling of price–quality relationships. *Computers & Operations Research*, 29(8), 951-969. https://doi.org/10.1016/S0305-0548(00)00096-4
15. Worzala, E., Souza, L. A., Koroleva, O., China, M., Becker, A., & Derrick, N. (2021). The technological impact on real estate investing: Robots vs humans: New applications for organizational and portfolio strategies. *Journal of Property Investment & Finance*, 39(2), 170-177. https://doi.org/10.1108/JPIF-12-2020-0137
16. Wu, H., Jiao, H., Yu, Y., Li, Z., Peng, Z., Liu, L., & Zeng, Z. (2018). Influence Factors and Regression Model of Urban Housing Prices Based on Internet Open Access Data. *Sustainability*, 10(5), 1676. https://doi.org/10.3390/su10051676
17. Lulin, X., & Li, Z. (2021). A new appraisal model of second-hand housing prices in China's first-tier cities based on machine learning algorithms. *Computational Economics*, 57(2), 617-637. https://doi.org/10.1007/s10614-020-09973-5
18. Truong, Q., Nguyen, M., Dang, H., & Mei, B. (2020). Housing Price Prediction via Improved Machine Learning Techniques. *Procedia Computer Science*, 174, 433–442. https://doi.org/10.1016/j.procs.2020.06.111
19. Federal Housing Finance Agency. House Price Index. (2024, September 1). https://www.fhfa.gov/
20. Fan, C., Cui, Z., & Zhong, X. (2018). House Prices Prediction with Machine Learning Algorithms. *Proceedings of the 2018 10th International Conference on Machine Learning and Computing - ICMLC 2018*. https://doi.org/10.1145/3195106.3195133
21. Phan, T. D. (2018). Housing Price Prediction Using Machine Learning Algorithms: The Case of Melbourne City, Australia. 2018 *International Conference on Machine Learning and Data Engineering (ICMLDE)*. https://doi.org/10.1109/icmlde.2018.00017
22. Mu, J., Wu, F., & Zhang, A. (2014). Housing Value Forecasting Based on Machine Learning Methods. *Abstract and Applied Analysis*, 2014, 1–7. https://doi.org/10.1155/2014/648047
23. Lu, S., Li, Z., Qin, Z., Yang, X., & Goh, R. S. M. (2017). A hybrid regression technique for house prices prediction. 2017 IEEE *International Conference on Industrial Engineering and Engineering Management (IEEM)*. https://doi.org/10.1109/ieem.2017.8289904
24. Zhan, C., Liu, Y., Wu, Z., Zhao, M., & Chow, T. W. (2023). A hybrid machine learning framework for forecasting house price. *Expert Systems With Applications*, 233, 120981. https://doi.org/10.1016/j.eswa.2023.120981

Vitaliy Kobets **Віталій Кобець**	DrSc (Economics), Professor of Computer Science & Software Engineering Department, Kherson State University, Kherson, Ukraine https://orcid.org/0000-0002-4386-4103 e-mail: vkobets@kse.org.ua Scopus Author ID: 56006224700 ResearcherID: G-8659-2018	Доктор економічних наук, професор, професор кафедри комп’ютерних наук та програмної інженерії, Херсонський державний університет, Херсон, Україна
Konstantin Fedchenko **Костянтин Федченко**	PhD Student of Computer Science & Software Engineering Department, Kherson State University, Kherson, Ukraine https://orcid.org/0009-0005-8988-0079 e-mail: f.kostya.o@gmail.com	Аспірант кафедри комп’ютерних наук та програмної інженерії, Херсонський державний університет, Херсон, Україна