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Research Article

Housing Demand Forecasting with Machine Learning Methods

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Abstract

Housing is a place where sustainable urban spaces are produced and where people's physical, cultural, environmental, economic, social, and psychological needs are evaluated together with their surroundings, rather than just a building where the need for shelter is met. With the acceleration of urbanization, new needs arise, and the first of these is the need for housing. The housing sector has become one of the most dynamic and continuous sectors associated with the increase in the need for housing. The need for adequate and accessible housing comes to the forefront in our country as well as in the world. Understanding and predicting the key features determining housing prices and value is an important consideration for urban planners and housing policymakers. In this study, Machine learning algorithms; Artificial Neural Network (ANN), Linear Regression (LR), Support Vector Machine (SVM), Gaussian Process Regression (GPR), and Regression Tree (RT) algorithm were used to predict the housing demand of Konya, and their forecasting performances were compared. According to the results obtained, the R^2 values of the methods are as follow; ANN is 0.94, SVM is 0.92, LR is 0.92, RT is 0.85, and GPR is 0.82. In this context, the ANN method gives the best estimation result for predicting housing demand. It was concluded that ANN is a better alternative for housing demand forecasting in Konya.

Keywords: Forecasting, Housing Demand, Housing Sales, Machine Learning

Makine Öğrenmesi Yöntemleri ile Konut Talep Tahmini

Öz

Konut sadece barınma ihtiyacının karşılandığı bina olmaktan ziyade, insanın fiziksel, kültürel, çecresel, ekonomik, sosyal ve psikolojik ihtiyaçlarının dikkate alınarak, çevresiyle birlikte değerlendirildiği sürdürülebilir kentsel mekanların üretildiği yerlerdir. Şehirleşme faaliyetlerinin hızlanmasıyla beraber yeni ihtiyaçlar ortaya çıkmakta bunların başında da konut ihtiyacı gelmektedir. Konut ihtiyacının artması ile beraber konut sektörü, en dinamik ve sürekli sektörlerden birisi haline gelmiştir. Yeterli ve erişilebilir konut ihtiyacı, dünyada olduğu gibi ülkemizde de öne çıkmaktadır. Konut fiyatlarını ve konut değerini belirleyen temel özellikleri anlamak ve tahmin edebilmek şehir planlaması yapanlar ve konut politikasını belirleyenler için önemli bir husustur. Bu çalışmada, Konya ilinin konut talebini tahmin etmek amacıyla makine öğrenmesi algoritmalarından, Yapay Sinir Ağı (YSA), Lineer Regrasyon (LR), Destek Vektör Makinesi (DVM), Gauss Proses Regresyonu (GPR) ve Regrasyon Ağacı (RA) modelleri kullanılmış ve tahmin performansları kıyaslanmıştır. Elde edilen sonuçlara göre yöntemlerin R^2 değerleri şu şekildedir; YSA 0,94, SVM 0,92, LR 0,92, RT 0,85 ve GPR 0,82'dir. Bu bağlamda konut talebini tahmin etmede en iyi tahmin sonucunu YSA yöntemi vermektedir. YSA'nın Konya ili konut talep tahmini için daha iyi bir alternatif olduğu sonucuna varılmıştır.

Anahtar Kelimeler: Tahmin, Konut Talebi, Konut Satışı, Makine Öğrenmesi

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1 Introduction

The construction and real estate sectors are at the forefront of the sectors in which Turkey is most successful in world competition. The construction sector in Turkey is constantly improving itself together with other sectors and continues to be in an important position in the country's economy [1]. At the same time, the construction and real estate sector is the second largest sector in Turkey, with the employment and the added value it creates [2].

Considering the urbanization rates in Turkey, the number of residents in province and county centers increased to 74 million 761 thousand in 2017. In 2017, the rate of urbanization in Turkey showed a great increase within the framework of the regulations and reached 92.5%. When the urbanization rate in the world was examined in the same year, it was seen that this rate was around 55% on average [3].

The need for the housing sector is increasing day by day due to various factors such as immigration, natural disasters, and the quality of the housing stock in our country. According to the address-based population registration system (ABPRS), assuming the current trends in population indicators will continue, Turkey's population will be 86 million 907 thousand 367 people in 2023. According to the National Address Database (NAD) data, the total number of residences in Turkey on 31 December 2017 was 32.7 million. Housing production takes place depending on the increase in the number of houses. Still, the need in the housing sector continues due to the different settlements, income groups, and household types. In this respect, it is essential to meet customers' housing needs [3,4].

In our country, it is essential to meet the need for adequate and accessible housing in certain cities and different population groups and to establish a sustainable supply-demand balance in the housing market [3].

The housing sector is one of the most dynamic and constantly developing sectors with an increasing need for housing [5]. Since the real estate sector is one of the most important components of the Turkish national economy today, the right solution to the housing demand not only ensures the modernization of the entire country's economy but also plays a vital role in the long-term stability of the entire society. The housing market can be affected by macroeconomic variables, spatial differences, community structure characteristics, and environmental possibilities [6]. Models or methods that try to analyze the market by imitating the thought processes of the players in the market are called advanced methods. Examples of advanced methods are Artificial Neural Networks (ANN), hedonic pricing, spatial analysis, fuzzy logic, etc. Examples of traditional valuation methods are the cost method, multiple regression method, and stepwise regression [7,8].

There are many studies on housing demand in the literature. As of 2022, there are 17,178 studies on housing demand and 473 studies on housing demand forecasting in the Web of Science database [9]. A keyword network analysis was performed using the VOSviewer (Version 1.6.9) package program to classify the housing demand studies more efficiently. The Web of Science database was used for the analysis. Other keywords used together with the housing demand keyword are shown in Figure 1. When Figure 1 is examined, it is seen that there are studies on the subject of housing demand, as well as on topics such as house prices, forecasting analysis, house supply, etc. As can be seen from the figure, it is seen that researchers have recently focused more on housing prices and housing supply. Therefore, in this study, research on housing demand forecasting was conducted.

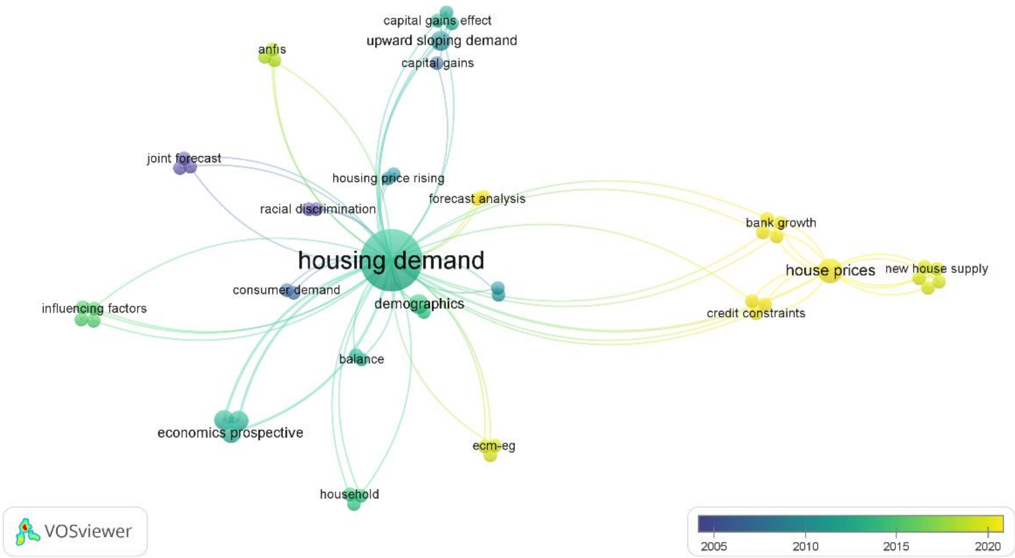

Figure 1. Housing demand keyword network analysis

Many studies have been carried out to solve the housing demand problem in Turkey and other countries of the world. In a study conducted for the estimation of house prices in Turkey, the estimation performance between hedonic regression (HR) and ANN models was compared, and it was concluded that ANN might be a better alternative for estimating house prices in Turkey [7]. A study conducted to predict housing prices in the province of Uşak using an ANN concluded that the model successfully predicted housing prices. As a result of the study, it was stated that the ANN could be presented as an intelligent decision-support suggestion mechanism for the optimum prices of housing sales [10]. In another study [11], the response of housing prices to changes in demand and supply-side variables across European countries was analyzed. The selection of these countries as a case study took into consideration such incorporation records, long- and short-term interest rates, housing price changefulness, and the monetary policy regime (including participation in ERM and EMU). The effect of macro factors on housing demand has been investigated. A supply and demand model has been proposed to solve the housing demand problem in selected European Union countries. In another study conducted to solve the housing demand problem in China, [12], has been reached that the residential area sold and the vacant housing area reflecting the housing supply and demand negatively affected the housing price, the land supply had a negative impact on the housing price, and the financial loan policy had a positive effect. In a review study, it was stated that non-traditional machine learning methods are suitable alternatives to regression-based methods. More recent research has focused on researching machine learning methods and their applicability to housing price prediction [13].

In this study, the province of Konya, the largest city in Turkey, was chosen. Because, The province of Konya's rich and deep-rooted history, safe location, agricultural industry, young population, urban life and culture, transportation network, and advantageous location is growing day by day. Parallel to this growth, there is also a vitality in housing sales. It is essential to accurately forecast the housing supply and demand to maintain this vitality. In this context, estimated monthly housing sales in Konya in this study. In 2021, the housing sales of Konya were approximately 2.55% of the housing sales of Turkey. Figure 2 shows the housing sales of Konya over the years [14]. According to the Address-Based Population Registration System (2021), the 2020-2023 population and population estimation results of Konya are shown in Table 1 [14].

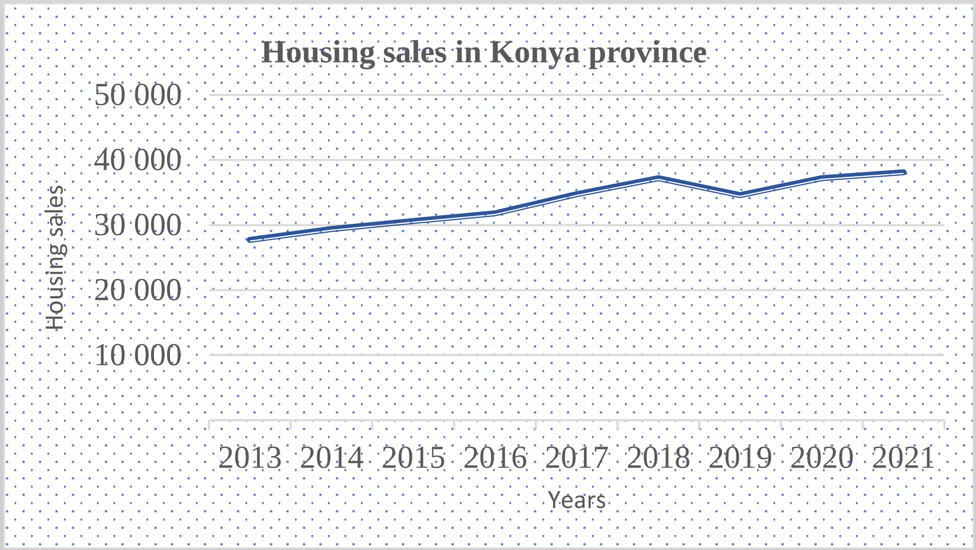

Figure 2. The housing sales of Konya over the years

Tablo 1. Province population estimation results of Konya in 2020-2023

Province	2020	2021	2022	2023	The population growth rate in 2023 compared to 2020 (%)
Konya	2.253.462	2.276.950	2.300.470	2.324.038	3,036

When Table 1 is examined, it is seen that the rate of increase in the population of 2023 compared to 2020 will be 3,036%. In order to contribute to the estimation of future housing sales and the formation of real estate policies, machine learning algorithms; ANN, Linear regression (LR), Support Vector Machine (SVM), Gaussian Process Regression (GPR), and Regression Tree (RT) algorithm for housing demand estimation of Konya were carried out. When the performances of ANN and machine learning methods were compared, it is concluded that ANN can be used as a better alternative method for housing demand forecasting in Konya.

2 Material and Method

2.1 Machine Learning

Machine learning is a sub-branch of artificial intelligence that enables computers to learn and act like humans with the help of algorithms and data. Machine Learning is concerned with studying, designing, and developing algorithms that allow computers to learn without being explicitly programmed [15].

The primary purpose of machine learning is to make accurate predictions. However, estimation functions can often be challenging to interpret and relate to a particular probability model. Researchers doing big data analysis use machine learning algorithms to obtain the desired information and make predictions [16]. Machine learning algorithms used in the study; ANN, Linear regression, Support vector machine (SVM), Gaussian process regression (GPR), and Regression tree algorithm.

Artificial Neural Network

The artificial neural network was first proposed by McCulloch and Pitts in 1943 [17]. ANN, which imitates the cognitive learning process of the human brain, can solve nonlinear problems such as prediction, optimization, recognition, and control, unlike classical computational methods [18].

Some statistical values of the criteria used in the study are shown in Table 2.

Table 2. Statistical values of the criteria

Criteria	Minimum	Maximum	Standard error	Skewness	Kurtosis
Years	2013	2021	0,249610	-1,09946E-16	-1,231221
Months	1	12	0,332836	0,006453	-1,20961
Interest rates for housing loans	9,65	23,16	0,322761	1,272244	0,823576
Consumer price index	216,74	686,95	10,664048	0,792412	-0,283099
Consumer confidence index	70,85	97,37	0,593975	-0,373325	-1,068516
Construction confidence index	50,85	99,36	1,017163	-1,522413	1,454354
Dollar exchange rate	1,76	13,53	0,224826	1,055842	1,006845
Industrial production index	77,04	165,56	17,073187	0,549336	0,421410

The magnitude of the skewness coefficient, whether positive or negative, indicates the magnitude of the skewness. The fact that the skewness coefficient is between ±0.00 is interpreted as not being excessively skewed. In addition, a skewness of ±1.50 is considered to have a normal distribution. The kurtosis coefficient expresses whether the bell curve showing the distribution of values is mesokurtosis, leptokurtosis, or platykurtosis. A kurtosis coefficient of 0 means that the bell curve is normal. A value greater than zero for the kurtosis coefficient means that the middle part of the bell curve is sharper than normal, and a value less than zero means it is flatter than normal [19].

The multi-Layer Sensor (MLA), a type of ANN, consists of the input layer, one or more hidden layers, and output layers. Each layer consists of interconnected neurons. Neurons collect the information from the outside with an additional function, pass it through the activation function, produce the output, and transmit it to the neurons in the next layer over the network connections. After the data transmitted to the network from the input layer are processed in the middle layer(s), the data go to the output layer. For the network structure to correctly determine the output (y) corresponding to the given inputs ($x_1, x_2,\ldots,x_n$), the weight values ($w_1, w_2,\ldots,w_n$) must be correctly determined, and an appropriate transfer function Tansig (Hyperbolic Tangent Sigmoid Transfer Function) used. Training the network is the process of finding the optimum values of the weights [20]. In this study, each input is multiplied by the weight value (w_{ij}) that connects that input to the processing element and combined through the addition function given in Equation 1[21]. Levenberg–Marquardt training algorithm was used because it is faster and more reliable than other training algorithms [22]. Figure 3 shows the cellular structure of the ANN [23]. The parameter values used while running the ANN method are given in Table 3.

$$net_j = \sum i \; x_i w_{ij} + b_j \quad (1)$$

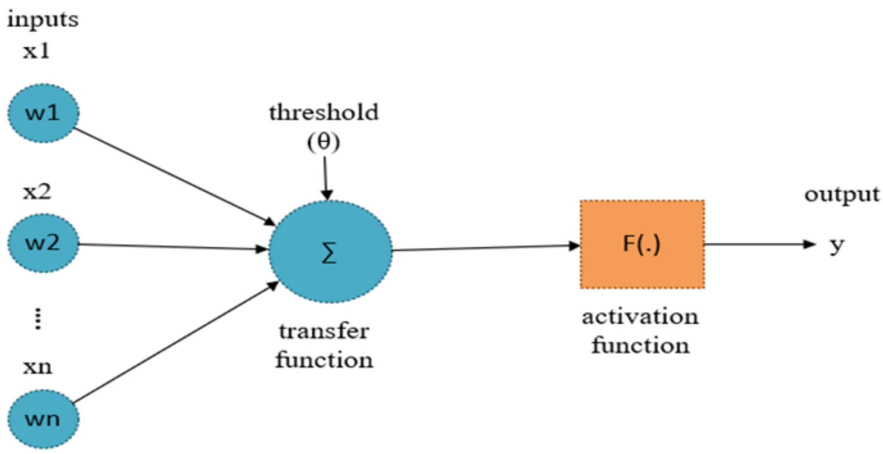

Figure 3. Artificial neural network cellular structure

Table 3. The parameter values used in ANN

Parameter	Value
Performance indexes	MSE, RMSE, MAE, MAPE, R^2
Maximum iteration during training	1000
Number of hidden layers	1
Neurons in the hidden layer	100
Activation function	Tansig
Training algorithm	Levenberg Marquardt
Number of input variables	8
Number of output variables	1
Splitting the dataset	70% (training), %15 (validation), %15 (test)

Linear regression (LR)

Regression analysis (RA) is an analysis method used to examine the numerical relationship between two or more variables. In regression analysis, it is called Simple Linear Regression if there are two variables, one dependent and one independent. It is called Multiple Linear Regression if there is one dependent and more than one independent variable. Multiple-variable regression analysis is the generalization of multiple linear regression analysis. There is more than one dependent variable in multiple-variable regression analysis [15]. A robust linear regression model, one of the linear regression models, was used in the application.

Support vector machine (SVM)

Support Vector Machines (SVM) is a robust supervised machine learning algorithm applied to classification and regression studies [24]. In general, SVMs divide the problems as linear and non-linear. It can only separate a few problems in daily life linearly [25]. The primary purpose of SVM is to create a model that indicates which group this observation should be in when a new observation is given using the algorithm developed for training data labeled according to two different groups [24]. The hyperparameter values used in the SVM method are given in Table 4.

Table 4. The hyperparameter values used in the SVM

Parameter	**Value**
Performance indexes	MSE, RMSE, MAE, MAPE, R^2
Kernel function	Quadratic
Kernel scale	1
Epsilon	0.01526
Box constraint	0.1526

Gauss process regression (GPR)

Gaussian process regression (GPR) is a non-parametric probability model [26]. Because this process is non-parametric, it tries to understand the correlation between all measured data rather than conforming to the variables of the chosen basis function [27]. GPR is a successful machine learning method generally preferred for solving nonlinear regression problems. GPR can produce successful results even with small data and has the features to measure uncertainty in predictions. Different covariance functions can be used to enable the most accurate option to be determined with GPR [28]. The hyperparameter values used in the GPR method are given in Table 5.

Table 5. The hyperparameter values used in the GPR

Parameter	**Value**
Performance indexes	MSE, RMSE, MAE, MAPE, R^2
Kernel function	Matern 5/2
Kernel scale	0.2442
Signal standard deviation	0.1264
Sigma	0.1264

Regression Tree (RT)

A regression tree is a decision tree algorithm that examines the relationships between dependent and independent variables and summarizes the results in a tree-like diagram [29]. The classification tree is defined in the literature as the decision tree used to classify certain classes or categorical data. Regression trees, on the other hand, are defined as decision tree models used in solving regression problems with continuous data [30]. The tree models used in Table 6 are compared according to their model flexibility characteristics [29]. Medium Tree models from regression tree methods were used in the study. The hyperparameter values used in the RT method are given in Table 7.

Table 6. Comparison of the regression tree

Tree Model	Model flexibility
Coarse Tree 	Low. Few leaves are used. The maximum number of divisions is 4.
Medium Tree 	Middle. A medium number of leaves is used. The maximum number of splits is 20.
Fine Tree 	High. A large number of leaves are used. The maximum number of splits is 100.

Table 7. The hyperparameter values used in the RT

Parameter	Value
Performance indexes	MSE, RMSE, MAE, MAPE, R^2
Tree model	Medium Tree
Minimum leaf size	12
The number of splits	10

One of the mathematical parameters used in evaluating the model in machine learning is the certainty coefficient [31]. The certainty coefficient (R^2) is a value that can be used in the performance measurement of the model that emerges depending on how much difference is between estimated and actual values. The closer results are to the actual value, the better the fit is considered. In the expression R^2, the result is always positive and takes a value in the range [0,1]. If the result is close to 1, the estimated value accurately explains the actual values [32].

Performance metrics

In this study, Coefficient of Determination (R2), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) evaluation methods were used to evaluate the estimation performance of the methods. Equations of the methods are given below [33]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i^*)^2}{\sum_{i=1}^{n}(y_i - y_{ave}^*)^2} \tag{2}$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^*)^2 \tag{3}$$

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n} \left| \frac{y_i - y_i^*}{y_i} \right| \tag{4}$$

$$\text{MAE} = \frac{\sum_{i=1}^{n}|y_i - y_i^*|}{n} \tag{5}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} | y_i - y_i^* |^2} \tag{6}$$

Here y_i represents the actual value, y_i^* represents the predicted value, y_{ave} represents the mean of the actual values, and n represents the total number of data.

3 Results and Discussion

This study compared machine learning algorithms' performances to predict monthly housing sales in Konya. When examining the studies in the literature, there are differences in the estimation parameters and methods discussed [8, 34, 35, 36]. In this study, within the framework of the existing literature, years, months, interest rates for housing loans, consumer price index, consumer confidence index, construction confidence index, dollar exchange rate, and industrial production index were determined as input parameters for the housing sales forecast in Konya. As the output parameter, the number of housing sales in Konya was considered. The artificial neural network model created to estimate the number of housing sales in Konya is shown in Figure 4.

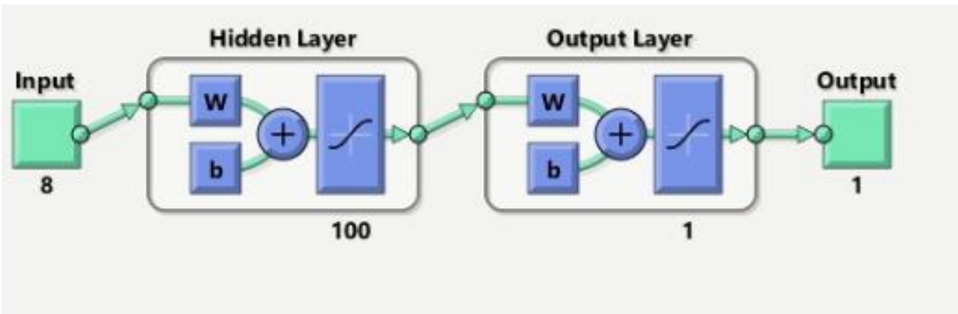

Figure 4. Artificial neural network model structure

The data of nine parameters constituting the input and output of the artificial neural network model were obtained from the Turkish Statistical Institute [37], and the Central Bank of the Republic of Turkey [38] covering the period 2013-2021 (2013 January-2021 December, the data set is given in the Appendix). Of the total data, 70% for training, 15% for testing, and 15% for validation were randomly allocated. Before training the network, input and output data should be normalized in the range of 0-1 (Equation 7) to be used in the machine learning methods.

$$X_{scaled} = \frac{X_n - X_{min}}{X_{max} - X_{min}} \tag{7}$$

MATLAB 2021a software was used to run the proposed ANN, LR, SVM, GPR, and RT models to estimate housing sales. Figure 5 shows the prediction performance of the machine learning models. When we examine Figure 5, it is seen that the predicted values of ANN are closer to the actual value than the other models.

Then, MSE, MAPE, MAE, and RMSE error indexes were calculated using Equations 3, 4, 5, and 6 for the performance measurement of the models and are presented in Table 8.

Table 8. Error indexes of the models

Method	R^2	RMSE	MSE	MAE	MAPE
SVM	0,92	0,031413	0,00098679	0,022464	2,2464
GPR	0,82	0,066438	0,0044139	0,049747	4,9747
LR	0,92	0,032143	0,0010322	0,028164	2,8164
RT	0,85	0,060217	0,0036261	0,049517	4,9517
ANN	0,94	0,057692	0,0033283	0,047132	4,7132

When Table 8 is examined that the R2-values of these models are calculated as 0.94, 0.92, 0.92, 0.82, and 0.85. When the prediction performances of machine learning models are compared by looking at the R2-values, this study showed that ANN might be a better alternative for estimating the number of housing sales in Konya. Statistical methods such as MSE, MAE, MAPE, RMSE, and R^2 are used to evaluate model performances in machine learning algorithms. However, the R^2-value provides more accurate results because there is no interpretability limit compared to other methods [39]. For this reason, the study's results were interpreted by considering the R^2-value, which expresses the relationship between the actual values and the predicted values. In this context, monthly housing sales for the province of Konya were made using the ANN method with the highest R^2-value for the next seven periods as follows; 1.992, 1.992, 1.987, 2.017, 2.041, 2.030, 2.089.

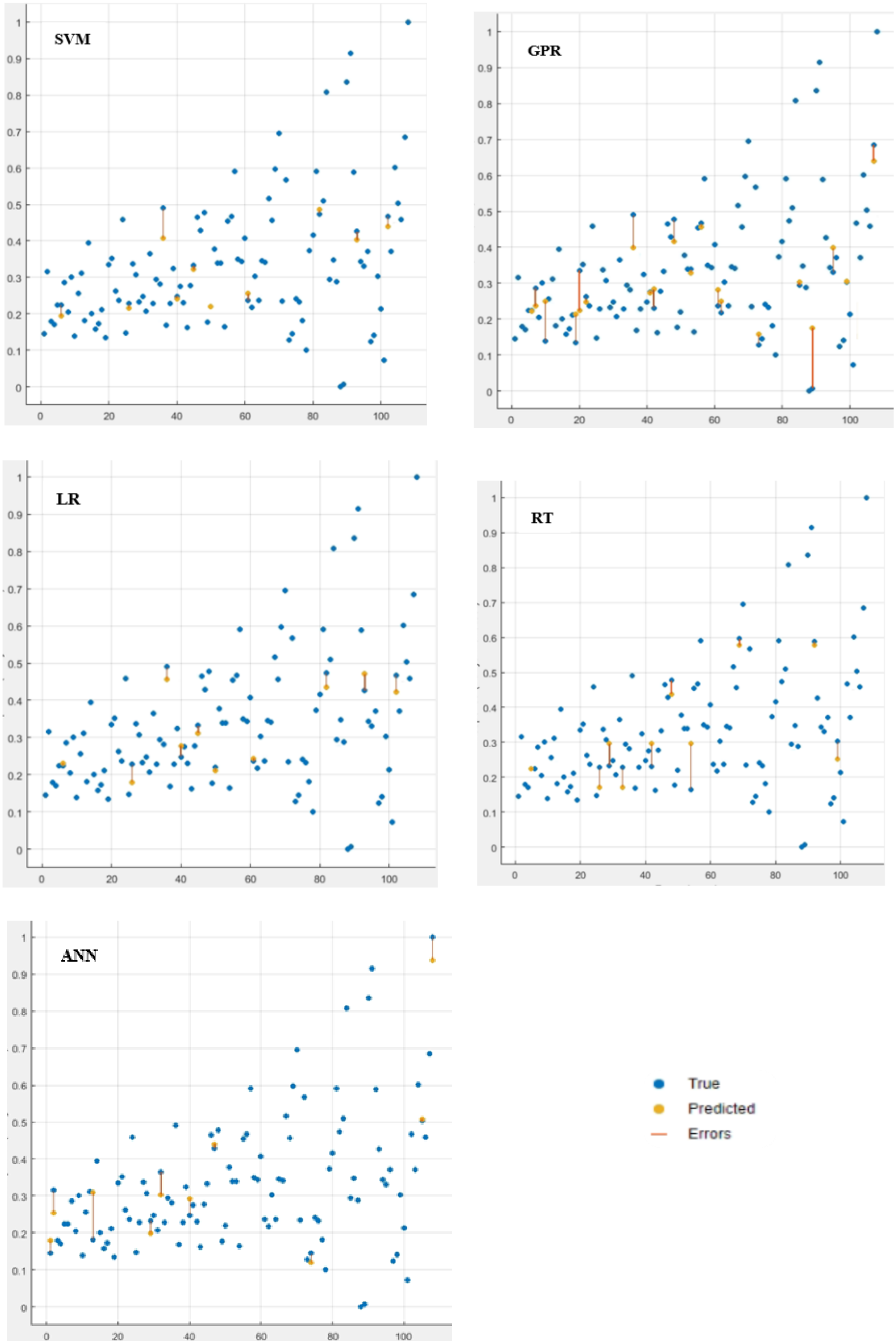

Figure 5. Prediction performance of the machine learning models

4 Conclusions

The construction sector has an essential share in economic development. The accuracy of the forecasts made primarily in the real estate sector in Turkey is of great importance in terms of macroeconomics. Therefore, accurate and reliable forecasting of housing sales will ensure that the supply and demand balance in the market is maintained. In addition, it will be possible to use resources more effectively with the help of detecting changes in demand in advance.

In this study, the number of housing sales was estimated using machine learning methods on the dataset created using the monthly data of dollar exchange rate, industrial production index, years, months, interest rates for housing loans, consumer price index, consumer confidence index, and construction confidence index covering 2013-2021 of Konya province. Among the demand forecasting methods, ANN gave the best results in terms of R^2 value is 0.94 in the study. In this context, it is seen that ANN performs better than machine learning methods applied in estimating housing demand for Konya.

Future studies can determine different independent variables to affect the demand. At the same time, increasing the prediction accuracy with other models can be investigated.

Ethics in Publishing

There are no ethical issues regarding the publication of this study.

Author Contributions

The authors contributed equally.

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Appendix

Years	Months	Interest rates for housing loans	Consumer price index	Consumer confidence index	Construction confidence index	Dollar exchange rate	Industrial production index	The number of housing sales in Konya
2013	1	12,02	216,74	91,52	93,1	1,76	78,2	1 909
2013	2	11,65	217,39	91,76	93,6	1,77	77,0	2 719
2013	3	11,32	218,83	92,06	99,0	1,81	85,9	2 072
2013	4	10,99	219,75	92,71	95,7	1,8	87,1	2 028
2013	5	10,66	220,07	95,53	97,0	1,82	91,9	2 280
2013	6	10,3	221,75	94,7	95,4	1,89	91,2	2 286
2013	7	10	222,44	96,54	94,5	1,93	93,7	2 579
2013	8	9,81	222,21	95,29	94,9	1,95	77,6	2 196
2013	9	9,7	223,91	91,43	93,3	2,02	96,3	2 645
2013	10	9,66	227,94	93,34	95,4	1,99	87,7	1 874
2013	11	9,65	227,96	96,78	94,8	2,02	100,4	2 433
2013	12	9,7	229,01	94,16	92,6	2,06	100,9	2 703
2014	1	9,82	233,54	91,54	99,4	2,22	87,5	2 080
2014	2	10,11	234,54	89,21	91,9	2,21	83,4	3 100
2014	3	10,46	237,18	92,43	88,6	2,22	93,9	2 177
2014	4	10,83	240,37	97,37	89,8	2,13	92,9	1 975
2014	5	11,18	241,32	95,11	91,8	2,09	94,3	2 045
2014	6	11,51	242,07	93,5	91,8	2,12	95,7	2 228
2014	7	11,73	243,17	93,73	90,1	2,12	90,6	1 863
2014	8	11,83	243,4	93,65	93,7	2,16	89,3	2 815
2014	9	11,85	243,74	94,02	95,1	2,2	102,3	2 889
2014	10	11,83	248,37	91,43	92,0	2,26	92,4	2 463
2014	11	11,86	248,82	90,87	93,7	2,23	100,1	2 350
2014	12	11,89	247,72	90,15	92,7	2,29	108,5	3 400
2015	1	11,87	250,45	89,35	93,6	2,33	86,7	1 924
2015	2	11,68	252,24	88,8	95,6	2,46	84,2	2 301

2015	3	11,46	255,23	86,49	94,0	2,58	99,7	2 818
2015	4	11,24	259,39	87,42	91,9	2,65	99,3	2 685
2015	5	11,12	260,85	86,8	95,5	2,65	98,8	2 329
2015	6	11,09	259,51	89,63	96,3	2,7	104,5	2 394
2015	7	11,16	259,74	88,24	93,3	2,69	95,1	2 203
2015	8	11,28	260,78	85,2	93,5	2,85	101,6	2 957
2015	9	11,5	263,11	82,15	91,4	3	97,1	2 303
2015	10	11,8	267,2	86,04	90,3	2,93	108,7	2 620
2015	11	12,07	268,98	95,15	95,9	2,87	107,5	2 558
2015	12	12,32	269,54	93,34	95,3	2,92	116,9	3 549
2016	1	12,59	274,44	91,95	95,3	3,01	91,3	2 024
2016	2	12,89	274,38	89,68	93,9	2,94	95,8	2 303
2016	3	13,2	274,27	89,87	92,0	2,89	106,4	2 758
2016	4	13,48	276,42	91,25	92,0	2,83	102,7	2 399
2016	5	13,68	278,02	91,7	90,9	2,93	107,1	2 530
2016	6	13,85	279,33	92,01	92,1	2,92	107,4	2 315
2016	7	13,96	282,58	89,66	93,3	2,96	86,9	1 986
2016	8	13,98	281,76	95,17	90,7	2,96	105,5	2 533
2016	9	13,86	282,27	94,78	92,4	2,96	93,5	2 798
2016	10	13,68	286,33	95,02	91,0	3,07	113,0	3 433
2016	11	13,48	287,81	91,41	87,2	3,27	113,7	3 256
2016	12	13,26	292,54	87,01	86,4	3,49	117,6	3 487
2017	1	13,03	299,74	88,39	85,7	3,73	97,1	2 060
2017	2	12,77	302,17	87,63	87,1	3,67	96,2	2 264
2017	3	12,49	305,24	89,89	96,1	3,67	113,2	3 010
2017	4	12,23	309,23	91,95	96,5	3,65	110,2	2 830
2017	5	12,03	310,61	94,22	98,0	3,56	113,7	2 832
2017	6	11,86	309,78	92,67	98,1	3,52	105,1	2 005
2017	7	11,72	310,24	93,21	96,4	3,56	112,5	3 383
2017	8	11,69	311,85	93,49	99,3	3,51	113,7	3 439
2017	9	11,75	313,88	92	94,6	3,47	110,6	4 030
2017	10	11,83	320,4	89,6	94,6	3,66	125,9	2 885
2017	11	11,95	325,18	87,35	93,2	3,88	125,0	2 854
2017	12	12,12	327,41	87,81	91,5	3,85	130,2	3 158
2018	1	12,35	330,75	92,38	97,1	3,77	109,2	2 343
2018	2	12,62	333,17	92,97	94,2	3,78	105,3	2 249
2018	3	12,93	336,48	92,28	89,0	3,88	120,7	2 661
2018	4	13,23	342,78	91,65	89,6	4,05	114,9	2 341
2018	5	13,42	348,34	90,95	89,0	4,41	121,1	2 866
2018	6	13,54	357,44	91,05	86,9	4,63	107,2	2 843
2018	7	13,94	359,41	92,92	88,2	4,75	120,9	3 678
2018	8	14,49	367,66	88,7	80,0	5,73	100,8	3 385
2018	9	15,51	390,84	81,15	67,4	6,37	114,8	4 058
2018	10	16,84	401,27	78,42	68,7	5,86	119,8	4 525
2018	11	18,13	395,48	80,95	66,8	5,37	116,2	2 335
2018	12	19,32	393,88	79,66	65,2	5,31	117,2	3 914

2019	1	20,33	398,07	80,11	66,4	5,37	101,0	1 832
2019	2	21,02	398,71	78,79	62,6	5,26	100,1	1 906
2019	3	21,3	402,81	81,1	63,3	5,44	115,1	2 369
2019	4	21,54	409,63	83,61	64,3	5,74	113,6	2 327
2019	5	22,09	413,52	77,05	60,7	6,05	121,0	2 083
2019	6	22,81	413,63	80,09	62,1	5,81	97,0	1 693
2019	7	23,16	419,24	78,94	64,4	5,67	120,4	2 998
2019	8	22,76	422,84	79,6	67,7	5,62	99,1	3 195
2019	9	21,74	427,04	77,64	72,6	5,71	119,5	4 030
2019	10	20,42	435,59	78,17	77,4	5,78	123,1	3 472
2019	11	19,12	437,25	81,24	75,4	5,73	121,0	3 643
2019	12	17,86	440,5	80,49	80,5	5,84	128,9	5 066
2020	1	16,66	446,45	81,12	89,5	5,92	108,7	2 616
2020	2	15,7	448,02	79,29	85,0	6,04	111,4	2 869
2020	3	15,14	450,58	80,98	87,5	6,31	114,0	2 585
2020	4	14,64	454,43	78,18	50,9	6,82	78,2	1 219
2020	5	13,87	460,62	82,85	68,3	6,95	84,1	1 250
2020	6	12,83	465,84	82,98	90,8	6,81	114,1	5 198
2020	7	11,83	468,56	82,82	99,3	6,85	119,6	5 572
2020	8	11,58	472,61	79,77	96,4	7,25	115,2	4 021
2020	9	11,67	477,21	81,91	95,1	7,51	133,1	3 245
2020	10	11,84	487,38	81,54	93,2	7,87	135,0	2 848
2020	11	12,06	498,58	79,98	90,1	8	131,5	2 790
2020	12	12,52	504,81	79,8	88,8	7,72	144,7	2 983
2021	1	13,06	513,3	82,87	84,2	7,39	116,6	1 803
2021	2	13,61	517,96	84,11	83,1	7,07	117,7	1 885
2021	3	14,14	523,53	86,63	79,8	7,63	137,0	2 657
2021	4	14,67	532,32	80,25	77,3	8,16	129,2	2 232
2021	5	15,22	537,05	77,53	79,6	8,34	117,2	1 565
2021	6	15,94	547,48	81,97	82,4	8,6	141,2	3 445
2021	7	16,67	557,36	80,09	86,3	8,61	117,8	2 984
2021	8	17,24	563,6	78,49	92,4	8,48	138,2	4 075
2021	9	17,55	570,66	79,6	91,8	8,51	144,9	3 609
2021	10	17,78	584,32	76,46	92,7	9,14	142,2	3 402
2021	11	17,9	604,84	70,85	93,6	10,52	150,6	4 480
2021	12	17,82	686,95	68,51	90,0	13,53	165,6	5 977