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Modelling the Unit Property Prices in Türkiye Employing Deep Learning Methods

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Abstract— The real estate market in Türkiye has witnessed significant growth and complexity in recent years necessitating advanced modelling techniques for accurate property price predictions. This paper presents a comprehensive study on the application of deep learning networks to model unit property prices across Türkiye, with a specific emphasis on its three major cities: Istanbul, Ankara, and Izmir. The unit property prices in the overall country and its three major cities are taken from the official resources and then the square meter unit property prices in USD are obtained. Then, a deep learning network is developed in Python programming language which accepts the lagged values of the unit property prices as input values. Then, the deep learning network is trained using the datasets separately for Türkiye and the three major cities. The loss curves of the deep learning network show a rapid convergence indicating the suitability of the developed deep learning network for the unit property price modelling. The actual and the modelled data are plotted indicating the accuracy of the developed model. Finally, the performance indicators of the developed deep learning model namely the coefficient of determination, mean absolute error, root mean square error and the mean absolute percentage error are computed verifying the high accuracy with R^2 values greater than 0.95 for all four modelling cases. The alternative utilization opportunities of the proposed deep learning model are also discussed in the conclusions section.

Keywords— Property prices, modelling, machine learning, deep learning, performance indicators.

I. INTRODUCTION

The real estate sector in Türkiye stands out as a vibrant and pivotal industry, reflecting the nation's economic dynamism and cultural diversity. In recent decades, Türkiye has undergone rapid urbanization, economic expansion, and a surge in population, resulting in a complex and multifaceted real estate environment. Gaining insights into the factors affecting unit property prices has become crucial for stakeholders such as policymakers, investors, and real estate professionals navigating this intricate market. This study seeks to make a unique contribution to the existing knowledge base by utilizing advanced deep learning networks to model unit property prices across Türkiye, with a specific focus on the three major cities – Istanbul, Ankara, and Izmir. The intricacies of the real estate market stem from a multitude of interconnected elements, including demographic shifts, economic metrics, urban development, and geopolitical considerations. Conventional models often struggle to capture the non-linear and dynamic relationships within such a complex environment. Deep learning, a subset of machine learning, emerges as a promising approach for handling intricate patterns and dependencies within extensive datasets. By employing sophisticated neural network architectures, the goal is to unveil hidden trends and complex relationships influencing unit property prices, providing a nuanced understanding of the Türkiye real estate market.

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As Türkiye experiences ongoing urbanization and economic growth, the need for accurate property price predictions becomes increasingly vital. Istanbul, Ankara, and Izmir, being the economic and cultural hubs of the country, represent microcosms of Türkiye's diverse real estate scenario. Modelling unit property prices in these major cities individually allows for a more detailed comprehension of local dynamics, contributing to both academic research and practical decision-making. This research, therefore, not only aims to deliver a comprehensive national model but also aims to explore the distinctive features of each major city, offering insights for localized strategies and policies. The significance of this investigation lies not only in its application of deep learning to real estate modelling but also in its potential to advance the broader understanding of economic dynamics and urban development in Türkiye. The outcomes of this study may serve as a valuable resource for decision-makers, investors, and real estate professionals, assisting them in making well-informed decisions in the rapidly evolving Türkiye real estate landscape. By combining the capabilities of deep learning with a city-centric approach, the objective is to unravel the complex factors influencing unit property prices, thereby contributing to the resilience and precision of real estate models in Türkiye.

The cities of Istanbul, Ankara, and Izmir present unique challenges and opportunities within the Türkiye real estate sector. Each city has its own set of socio-economic dynamics, urban development patterns, and cultural influences that shape the local property market. Through the lens of deep learning, we intend to decipher the intricate interplay of these factors and their impact on unit property prices in each city. This city-specific approach not only enhances the granularity of our analysis but also provides stakeholders with actionable insights tailored to the distinct challenges posed by the real estate markets in these major urban centers. Moreover, the integration of deep learning into real estate modelling holds the promise of enhancing the adaptability and predictive accuracy of the models. Traditional approaches often struggle to adjust to the dynamic nature of the Türkiye real estate market, where factors such as changing consumer preferences and evolving economic conditions play a pivotal role. Deep learning, with its ability to learn from complex data patterns, offers a more flexible framework that can evolve alongside the ever-changing real estate landscape, contributing to a more robust and reliable predictive model for unit property prices in Türkiye and its major cities.

This paper provides an in-depth investigation into the utilization of deep learning networks for modelling unit property prices throughout Türkiye, with a specific focus on its three primary cities: Istanbul, Ankara, and Izmir. Official resources are employed to gather unit property prices in both the entire country and its major cities, subsequently converting them into square meter unit property prices in USD. Subsequently, a Python-based deep learning network is developed, which takes lagged values of unit property prices as input. The network undergoes separate training phases for Türkiye as a whole and its three major cities. The loss curves exhibit rapid convergence, affirming the applicability of the developed deep learning network for unit property price modelling. Graphical representations of actual versus modelled data are presented, underscoring the precision of the model. To validate the accuracy of the developed deep learning model, performance indicators, including the coefficient of determination, mean absolute error, root mean square error, and mean absolute percentage error, are computed. Remarkably, the R2 values exceed 0.95 in all four modelling cases, affirming the high accuracy and reliability of the developed deep learning model in capturing the intricacies of unit property prices in Türkiye and its major cities.

II. Literature Survey

The application of machine learning (ML) in modelling property prices has garnered significant attention in recent literature. For example, the property prices in Boston area is modelled using support vector machine (SVM), least squares support vector machine (LSSVM), and partial least squares (PLS) methods in [1] where it is concluded that the SVM and LSSVM approaches can model the nonlinearity of the property prices compared to the PLS approach. In another work, the property values in Malaysia are modelled utilizing boosted regression trees (BRT), linear regression and nonlinear regression analyses and it is shown that the BRT algorithm performs better compared to the regression methods [2]. The housing prices in the Fairfax County, Virginia are modelled in another study considering the prices of 5359 houses using naïve Bayesian, adaptive boosting (Adaboost) and the RIPPER (Repeated Incremental Pruning to Produce Error Reduction) methods where it is demonstrated that the RIPPER method performs better than the other considered approaches [3]. A predictive software is developed using linear regression and gradient boosting algorithms in [4] in which the coefficient of determination value of 0.92 is reported. In another work, the machine learning algorithms of Support Vector Regression (SVR), K-Nearest Neighbor (K-NN) and Principal Component Regression (PCR) are utilized for the prediction of the property prices in the USA where it is concluded that the PCR has the best performance [5]. The housing prices in the UK is investigated in another study where the Gaussian process regression, regression-kriging, random forests and an M5P decision tree algorithms are compared and it is shown that the Gaussian process regression has the best accuracy [6]. In another work, the property prices in Santiago, Chile are modelled using neural networks, random forest search and SVM approaches considering over 16000 houses and it is concluded that the random forest method has the best performance [7]. The housing prices in Poland considering 12438 properties are modelled in another work using linear regression, decision trees and neural network methods where it is shown that the decision tree approach provides the best accuracy [8].

The property prices in Australia have been modelled employing random forest, decision tree and ensemble neural networks in another work with 1967 housing data where the random forest approach is found to be the most accurate method [9]. In another study, the linear regression method and the gradient boosting approach are compared for the modelling of the property prices in China considering 253 units where it is demonstrated that the gradient boosting method is more accurate [10]. The SVM methodology is applied for the modelling of the housing prices in Japan for 6320631 advertisements where it is shown that the SVM approach is an effective method for the property price modelling [11]. The three types of regression namely the linear regression, multivariate regression and the polynomial regression are utilized for the modelling of the housing prices in India considering 21000 properties and it is found out that the mixture of these three methods performs the best [12]. Similarly, the linear regression, random forest and the gradient boosting algorithms are used for the modelling of the warehouse prices in Beijing considering 25900 properties where it is shown that the random forest approach provides the best accuracy [13]. In another study, the performances of the linear regression, random forest and the PCR methods are evaluated for the modelling of the property prices in Serbia considering 7407 units where it is concluded that the random forest algorithm has the best accuracy [14]. The housing prices in Mumbai, India have been modelled using linear regression, random forest and neural network regression in another work where it is shown that the neural network regression has the best performance indicators [15]. The Swedish housing prices are modelled in another work considering 57974 units using linear regression, random forest, neural network regression and the SVM methods and it is concluded that the random forest method provides the most accurate results [16].

The housing prices in Montreal, Canada are modelled using linear regression, k-nearest neighbour, random forest and SVM methods considering the price data of 25000 properties and it is shown that the k-nearest neighbour provides the best accuracy [17]. In another work, the property prices in China is modelled using linear regression, SVM regression, neural network regression and the k-nearest neighbour approach and it is shown that the SVM regression has the best performance indicators [18]. Similarly, the housing prices in Malaysia is modelled using random forest, decision tree, lasso regression, ridge regression and linear regression and it is concluded that the random forest approach has the best accuracy [19]. Similarly, the property values in Kota Bharu, Malaysia are modelled using various regression models where it is demonstrated that the rank transformation regression model has better performance compared to the ordinary least squares model [20]. The housing prices in Gangnam, South Korea are modelled utilizing random forest approach and the conventional hedonic modelling method and it is shown that the prediction errors of the random forest model and the ordinary least squares model are on the order of 5% and 20%, respectively [21]. In an extensive study, many machine learning models namely the random forest, extreme gradient boosting, light gradient boosting machine, hybrid regression and the stacked generalization regression approaches are used to model the housing prices in Beijing, China and it is concluded that the hybrid regression has the best accuracy [22]. In another study, the modelling of property prices in Dortmund, Germany employed both the ordinary least squares regression and the spatial lag model where the findings indicate that the spatial lag model, which considers the prices of nearby residences, is a significant factor in explaining residential housing prices [23]. The gradient boosting decision tree (GBDT) method is utilized in another work where the nonlinear effects on the housing prices in Shanghai, China are

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modelled and it is shown that the GBDT model can be used to model the housing prices considering nonlinear relationships [24].

The property prices of about 40000 houses in Hong Kong are modelled in another work where machine learning algorithms namely the random forest, SVM and the GBM methods are utilized and the performance indicators imply that the random forest and the GBM methods outperform the SVM algorithm [25]. The optimization of the weights of the ensemble machine learning methods are studied in another work where the housing prices of Boston and Ames areas are considered where it is concluded that optimized ensemble networks provide high accuracy for the prediction of the housing prices [26]. Similarly, least squares support vector regression, classification and regression tree, general regression neural networks and the backpropagation neural networks are utilized for the forecasting of the housing prices in which the results of the least squares support vector regression provides the best accuracy [27]. In an extensive study, the property prices in 100 major cities of China are modelled using the variations of the neural network architectures and it is found out that a simple four delay neural network having three hidden layers provide 1% RMSE [28]. In another work, the cost-sensitive deep forest algorithm is developed for the property price prediction by considering the problem as a classification problem, the developed approach is tested on the prices of 1460 houses with 79 features and it is shown that the developed cost-sensitive deep forest algorithm provides the best accuracy [29]. In another work, the house price appreciation rate is modelled using machine learning methods considering the visual features extracted from street view images and the house photos where it is shown that the deep learning methods provide accurate prediction of the house price appreciation rates [30]. The property prices during the Covid-19 pandemic are modelled using 15 different machine learning algorithms considering the prices of 18992 houses and it is concluded that the extreme gradient boosting algorithm has the best accuracy among the considered 15 machine learning methods [31]. In another extensive study, the property prices are modelled using several methods namely linear regression, least absolute shrinkage and selection operator regression, ridge regression, k-nearest neighbour regression, decision tree regression and extra trees regression algorithms where it is shown that the extra trees regression outperforms the other methods with a coefficient of determination value of 0.63 [32].

III. MODELLING DETAILS AND RESULTS

First of all, the square meter unit property prices in USD are calculated from the data gathered from the official sources. The square meter unit property prices in USD for Istanbul, Ankara, Izmir and the whole Türkiye are given in Fig. 1, Fig.2, Fig. 3 and Fig. 4, respectively.

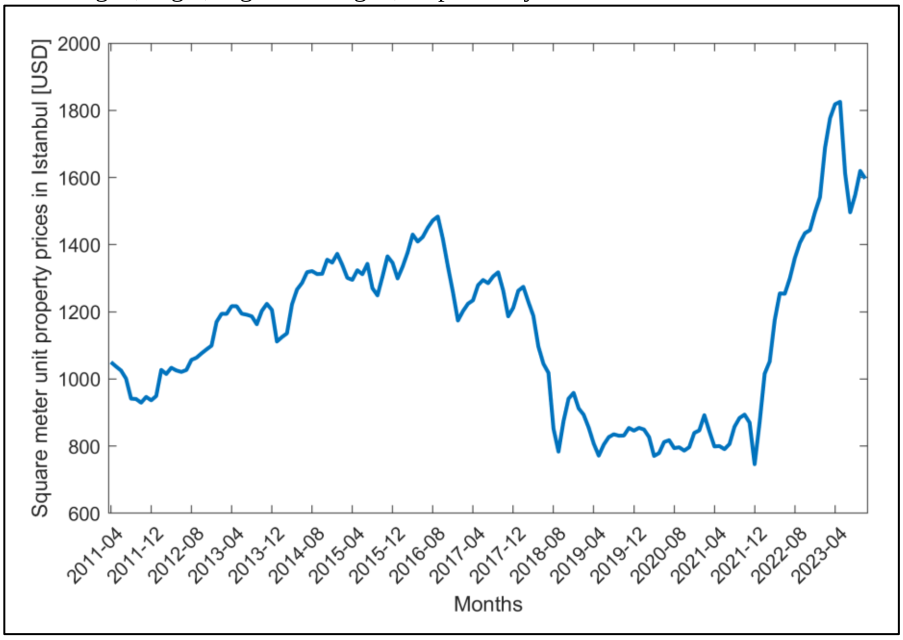

Fig. 1 The square meter unit property prices in Istanbul

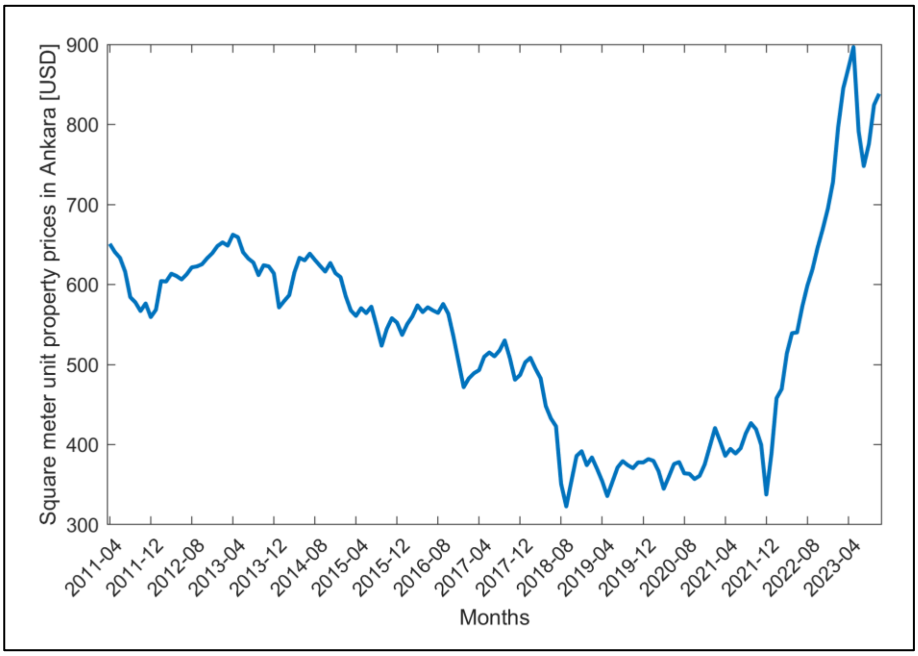

Fig. 2 The square meter unit property prices in Ankara

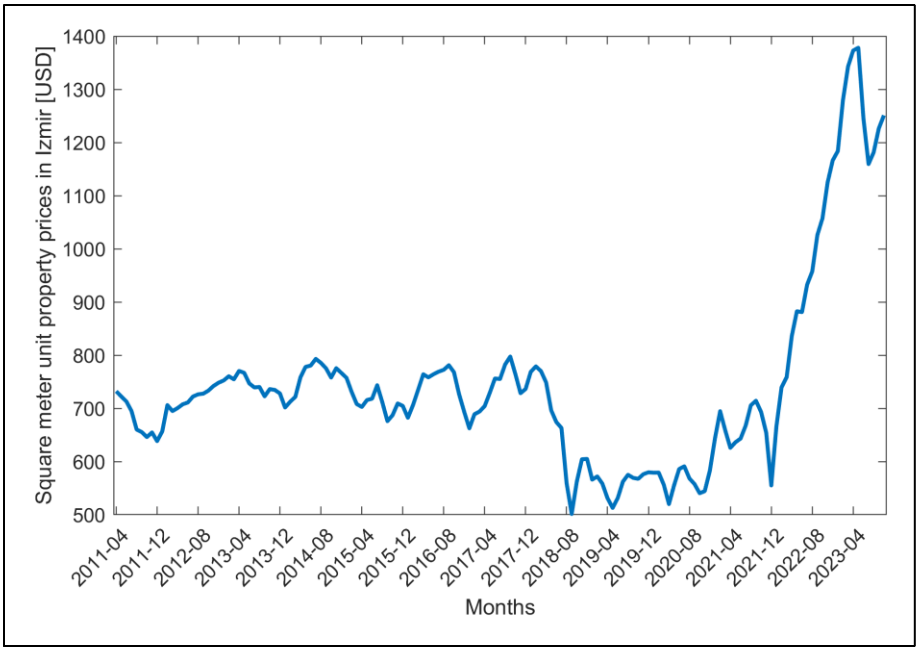

Fig. 3 The square meter unit property prices in Izmir

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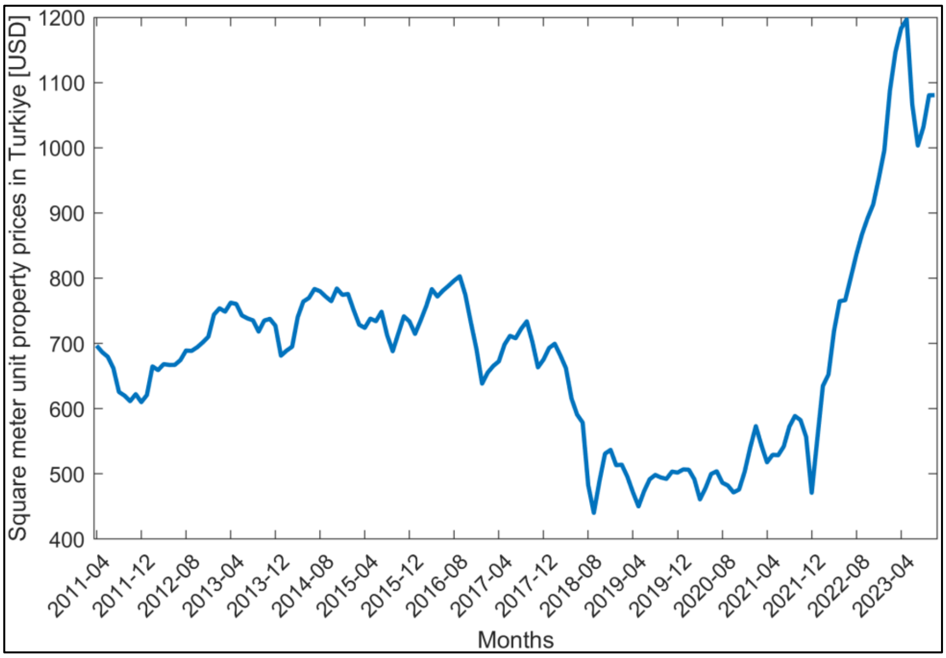

Fig. 4 The square meter unit property prices in overall Türkiye

A deep learning network model consisting of 2 hidden layers each having 15 neurons is developed for the modelling of the unit property prices in Istanbul, Ankara, Izmir and the overall Türkiye. The structure of the developed deep learning network is shown in Fig. 5.

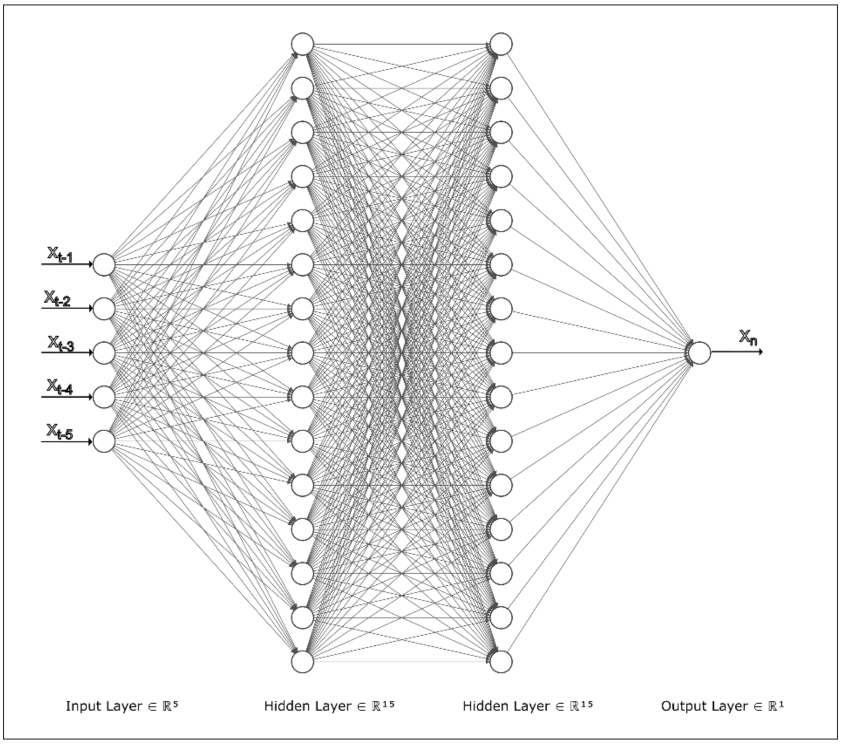

Fig. 5 The developed deep learning model for the modelling of the unit property prices

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The developed deep learning network model is trained for the unit property prices in Istanbul, Ankara, Izmir and the overall Türkiye separately. The 30% of the available data is used as the training data where the remaining 70% is utilized as the test data [33]. The MLPRegressor class in Python is used as the deep learning tool [34]. The loss curves obtained during the training phases of the unit property prices of Istanbul, Ankara, Izmir and the overall Türkiye are given in Fig 6, Fig. 7, Fig. 8 and Fig. 9, respectively.

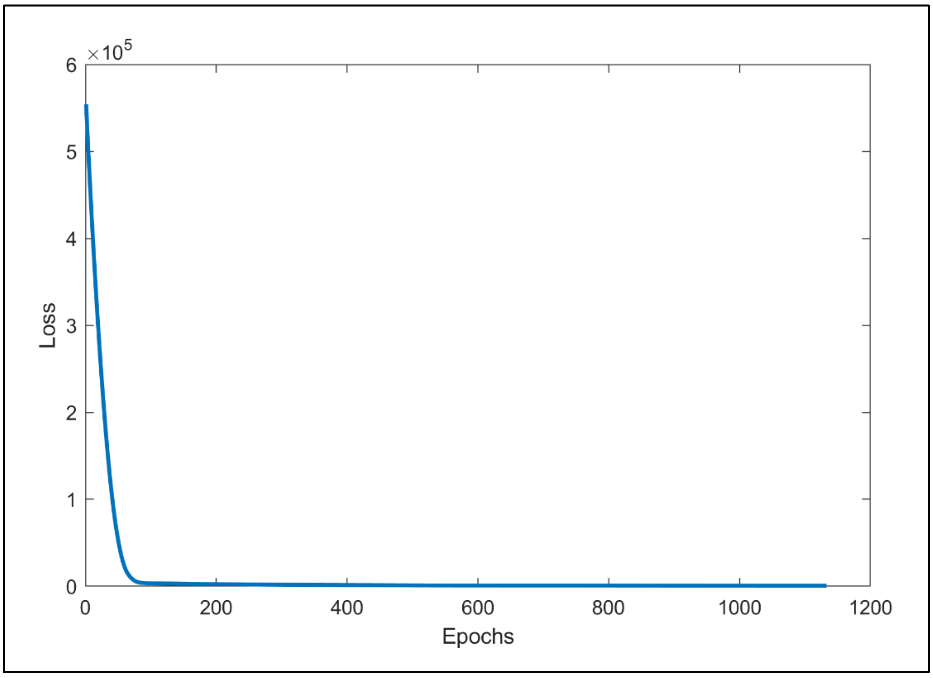

Fig. 6 The loss curve of the training phase of the unit property prices data in Istanbul

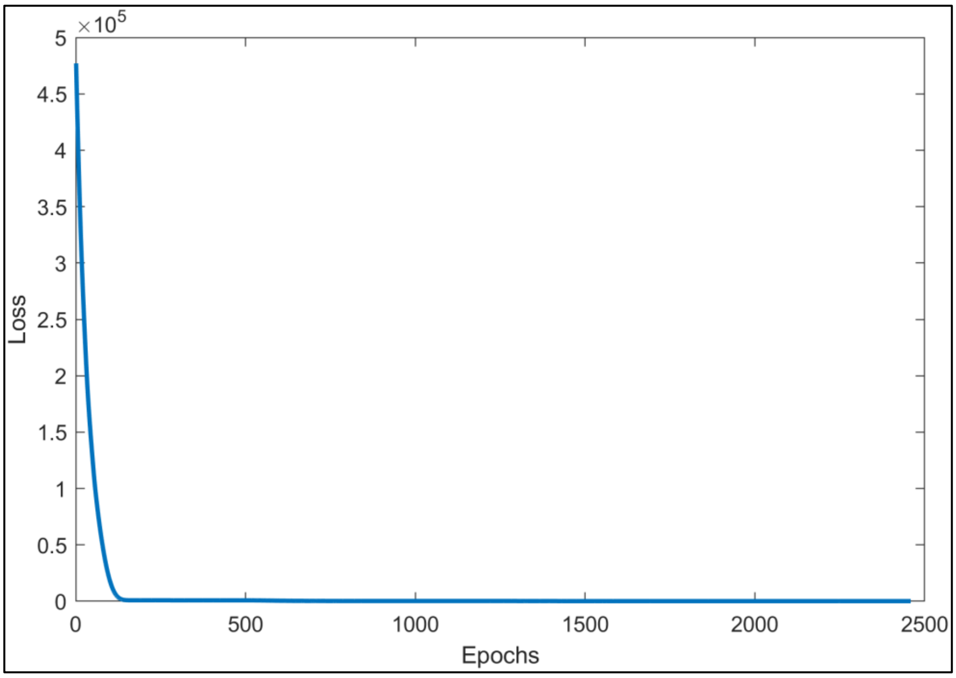

Fig. 7 The loss curve of the training phase of the unit property prices data in Ankara

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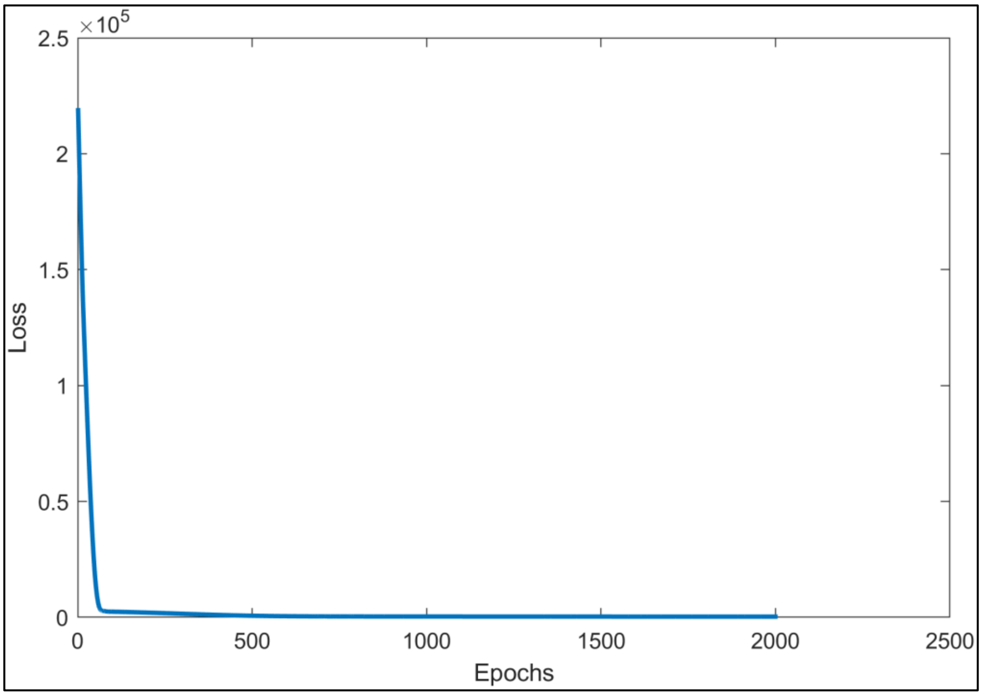

Fig. 8 The loss curve of the training phase of the unit property prices data in Izmir

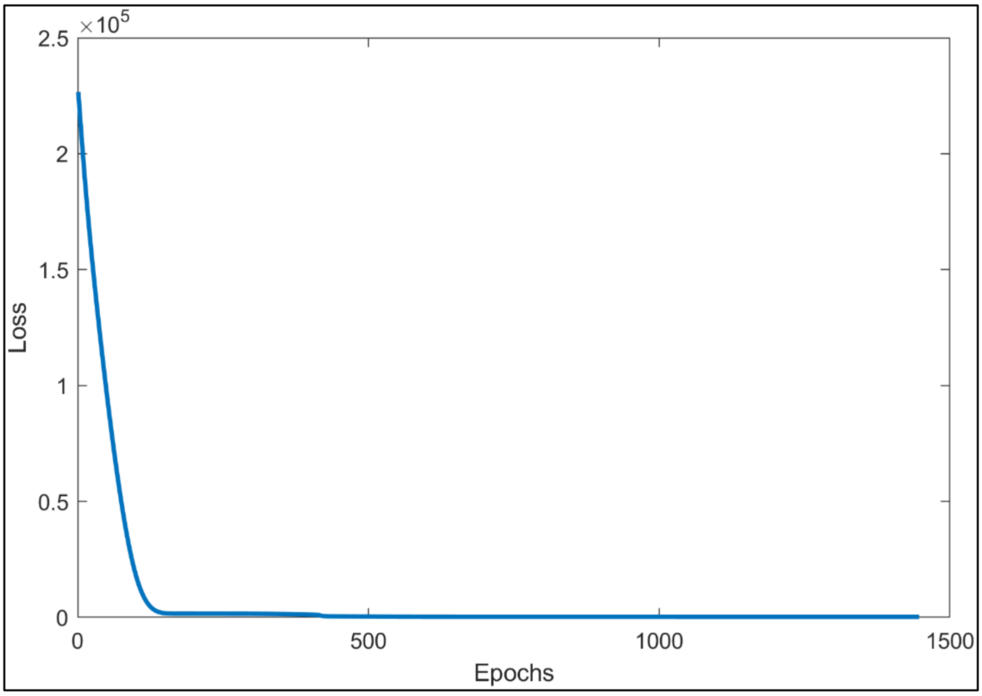

Fig. 9 The loss curve of the training phase of the unit property prices data in overall Türkiye

As it can be observed from Figs. 6-9, the developed deep learning model is trained for the unit property prices of Istanbul, Ankara, Izmir and the overall Türkiye rapidly. The actual unit property prices and their

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corresponding deep learning results for Istanbul, Ankara, Izmir and overall Türkiye are then plotted in Fig. 10, Fig. 11, Fig. 12 and Fig. 13, respectively.

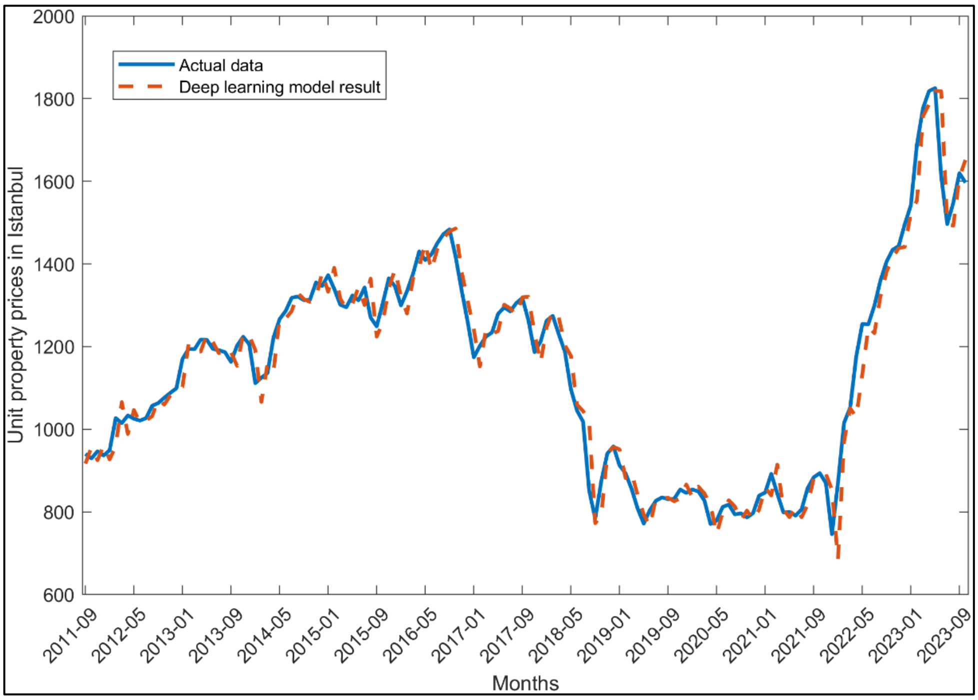

Fig. 10 The unit property prices in Istanbul (solid line: actual data, dashed line: deep learning model result data)

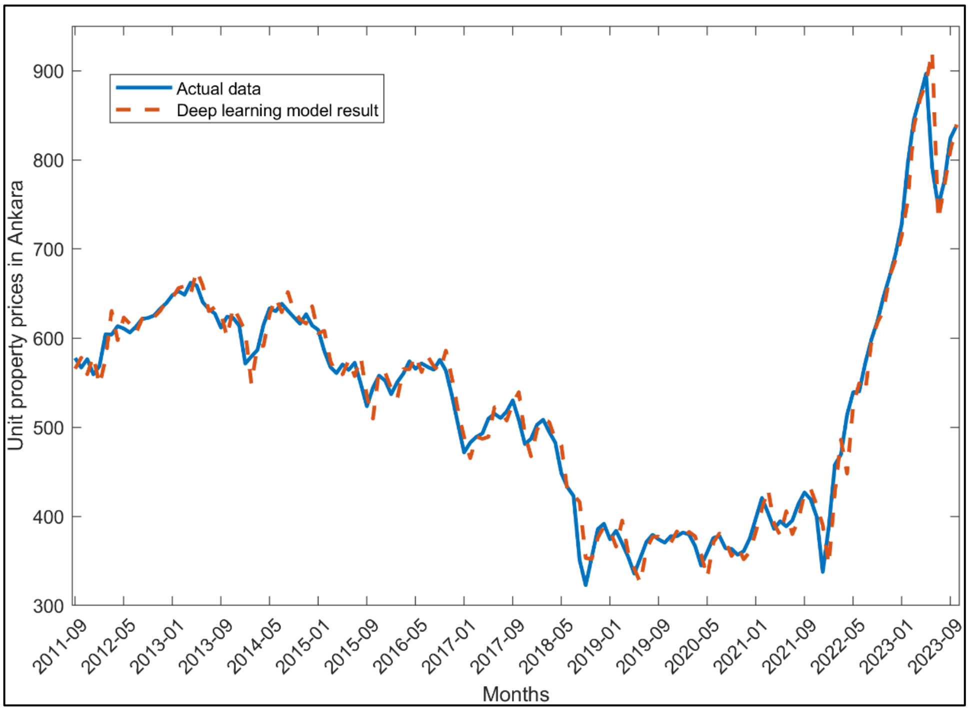

Fig. 11 The unit property prices in Ankara (solid line: actual data, dashed line: deep learning model result data)

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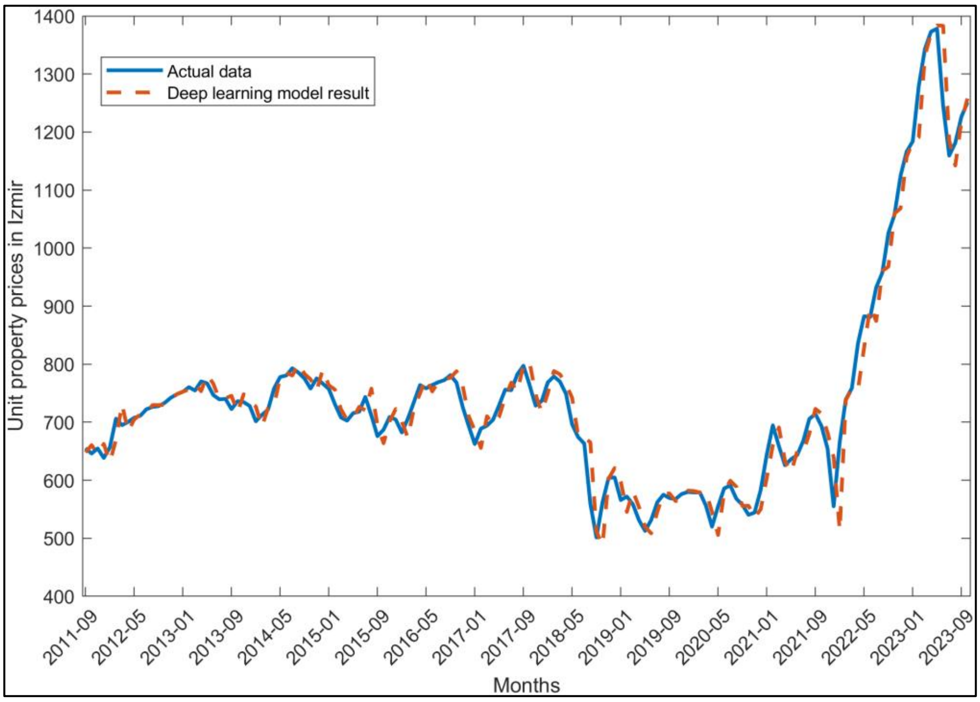

Fig. 12 The unit property prices in Izmir (solid line: actual data, dashed line: deep learning model result data)

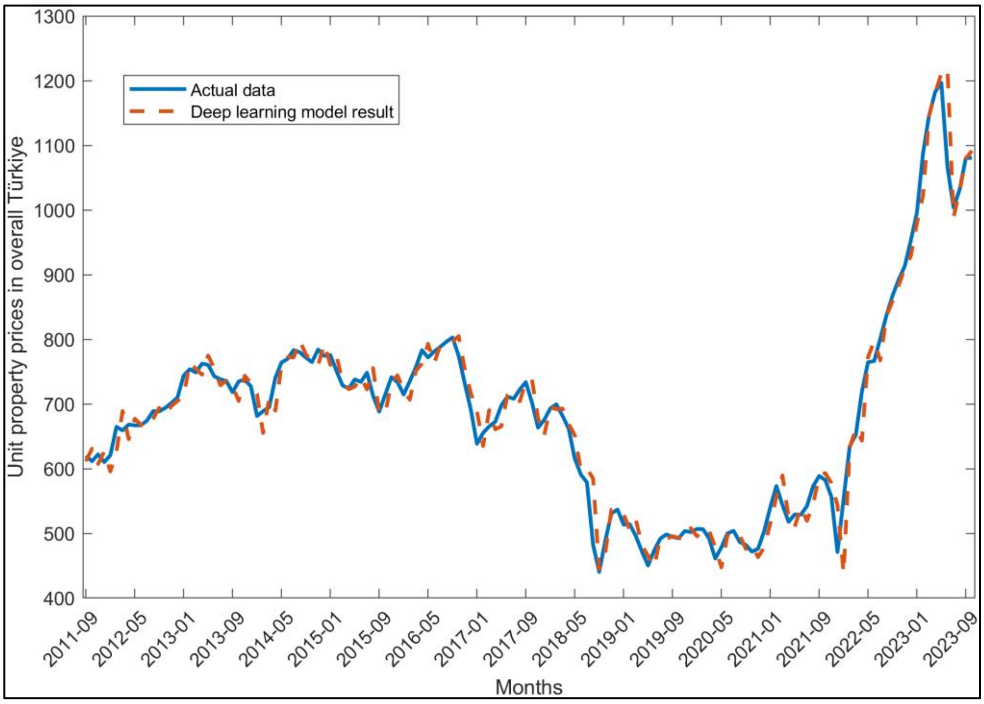

Fig. 13 The unit property prices in overall Türkiye (solid line: actual data, dashed line: deep learning model result data)

As it can be seen from Figs. 10-13, the developed deep learning model successfully models the unit property prices in Istanbul, Ankara, Izmir and overall Türkiye. In order to further clarify the performance of the developed model, the root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage

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error (MAPE) and the coefficient of determination (R^2) values are calculated for the data modelling for the unit prices in Istanbul, Ankara, Izmir and the overall Türkiye using the following equations [35]:

$$RMSE = \sqrt{\frac{\sum_1^d (O-M)^2}{d}} \tag{1}$$

$$MAE = \frac{\sum_1^d |O-M|}{d} \tag{2}$$

$$MAPE = \frac{100}{d}\sum_1^d \left|\frac{O-M}{M}\right| \tag{3}$$

$$R^2 = \frac{\sum_1^d (O-avg(O))^2 - \sum_1^d (O-M)^2}{\sum_1^d (O-avg(O))^2} \tag{4}$$

where *O* is the actual data, *M* is the data obtained from the developed deep learning model and *d* is the length of the data. The calculated RMSE, MAE, MAPE and R^2 values are given in Table 1.

TABLE I
PERFORMANCE PARAMETERS OF THE DEVELOPED MODEL

Performance metric \ Data type	Data of unit property prices in Istanbul	Data of unit property prices in Ankara	Data of unit property prices in Izmir	Data of unit property prices in overall Türkiye
RMSE	47.83	20.64	31.15	27.35
MAE	33.01	14.21	20.42	17.86
MAPE	0.02	0.02	0.02	0.02
R^2	0.96	0.97	0.96	0.96

As it can be observed from Table 1, the developed deep learning model accurately models the unit property prices in Istanbul, Ankara, Izmir and overall Türkiye with R^2 values greater than 0.95 indicating the high performance of the developed deep learning model.

IV. CONCLUSIONS

This study conducts a comprehensive examination of the application of deep learning networks in modelling unit property prices across Türkiye, with particular attention to its three main cities: Istanbul, Ankara, and Izmir. Official data sources are utilized to collect unit property prices both nationwide and in the major urban centers, which are then converted into square meter prices in USD. Subsequently, a Python-based deep learning network is constructed, incorporating lagged values of unit property prices as inputs. The network undergoes distinct training phases for Türkiye overall and its three major cities. The convergence of loss curves is observed, indicating the effectiveness of the developed deep learning network for modelling the unit property prices. Visual representations comparing actual and modelled data are presented, highlighting the accuracy of the model. To assess the validity of the deep learning model, various performance metrics such as the coefficient of determination, mean absolute error, root mean square error, and mean absolute percentage error are calculated. Remarkably, the coefficient of determination values surpass 0.95 in all four modelling scenarios, demonstrating the high accuracy and reliability of the developed deep learning model in capturing the complexities of unit property prices in Türkiye and its key urban areas.

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