International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-15 Issue-11, October 2026

Application of Transformer Model in Predicting Housing Price in Selected Vietnamese Provinces

Phan Thi Ha, Tran Thi Thuy Ha

Abstract: ***This paper selects an appropriate machine learning model to forecast real estate and apartment prices across several major provinces and cities in Vietnam. While we primarily deploy the Transformer, we also experimented with other machine learning algorithms, such as Linear Regression, Decision Tree, and Random Forest, to demonstrate the Transformer's superior performance. We automatically collected raw data from Vietnam's largest real estate website and then preprocessed, analysed, and evaluated it. The analysis revealed that building a prediction model on a single dataset yields fewer effective results than splitting the data into two distinct sets, one for landed properties and the other for apartments, and developing separate models for each product category. Building two independent prediction models allows effective use of each product type's unique characteristics, improving the accuracy and efficiency of machine learning for real estate price prediction.***

Keywords: Linear Regression, Decision Tree, Random Forest, Transformer, Classification, Prediction, Forecasting, Apartments, Houses, Real Estate.

I. INTRODUCTION

E-commerce has driven the growth of real estate trading platforms, offering benefits such as faster transactions, more diverse choices, and greater price transparency. This benefits both sellers and buyers; however, they still face challenges caused by multidimensional information. For instance, a product's price may be posted on multiple platforms, making it difficult to aggregate, cross-reference, and compare data. Additionally, some brokers inflate prices above market rates to secure higher commissions.

In recent years, Vietnam's real estate and housing policies have changed significantly in scope and planning to support socio-economic development. As a result, real estate prices have been significantly impacted. According to the Vietnam Real Estate Association, real estate prices in 2025 dramatically increased compared to 2019, especially in major cities and provinces [10].

Manuscript received on 22 September 2026 | First Revised Manuscript received on 30 September 2026 | Second Revised Manuscript received on 06 October 2026 | Manuscript Accepted on 15 October 2026 | Manuscript published on 30 October 2026

*Correspondence Author(s)

Dr. Phan Thi Ha*, Lecturer, Faculty of Information Technology, Posts and Telecommunications Institute of Technology (PTIT), Ha Noi, Vietnam, and Computing Fundamentals Department, FPT University, Hanoi, Vietnam. Email: hapt@ptit.edu.vn, hapt37@fe.edu.vn , ORCID ID: 0009-0003-2521-0717

Dr. Tran Thi Thuy Ha, Lecturer at the Faculty of Electronics Engineering at Posts and Telecommunications Institute of Technology (PTIT) in Ha Noi, Vietnam. Email: hatt@ptit.edu.vn, thuyhadt@gmail.com, ORCID ID: 0009-0005-6734-1509

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Rapid changes and price fluctuations make it difficult for buyers to determine the true value of properties. Sellers also face challenges in setting prices that are neither significantly below nor above market levels.

Therefore, predicting real estate prices is necessary because it helps market participants make more accurate, objective decisions. Currently, many machine learning models have been applied to solve this problem, including Linear Regression, Decision Tree, and Transformer [3,4,7,8]. In Vietnam, several studies have used machine learning models to forecast real estate prices and have achieved promising results. However, recent reviews of related work [7,10] show that applying Transformer models to forecast real estate prices in Vietnam remains limited and has not yet been studied comprehensively and systematically on a diverse dataset.

In this study, we investigate and experiment with different machine learning models, including Linear Regression [5], Decision Tree [1], Random Forest [2], and Transformer, to predict real estate prices in Vietnam. Training data were collected from the Batdongsan.vn website [9], one of the major real estate trading platforms in Vietnam, with rich and dynamic data from 10 key provinces and cities: Hanoi, Ho Chi Minh City, Da Nang, Binh Duong, Hai Phong, Dong Nai, Khanh Hoa, Bac Ninh, Long An, and Quang Ninh.

During data collection, the research team evaluated and selected the curr_cffi library as a suitable data-crawling tool because it can effectively emulate browser behaviour and reduce the impact of anti-crawling mechanisms. After collection, the team reviewed the data to detect and remove duplicates. Then, the team preprocessed, analysed, explored, and standardised the data to improve quality before using it for model training and evaluation. Subsequently, we developed and trained a Transformer model to address the real estate price prediction task. We evaluated model performance using appropriate metrics and compared it with traditional machine learning methods. In practice, few applications can estimate real estate value based on specific features such as number of bedrooms, area, house direction, frontage, road width, number of bathrooms, and legal status. Therefore, there is a strong need for an objective application that can help buyers and sellers accurately estimate the prices of the properties they are interested in.

II. METHODOLOGY

A. Crawl Data from Website

A dedicated tool for automatically collecting raw data from Batdongsan.vn, a major real estate trading platform in Vietnam, has been developed. The tool accesses data by province and

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city and collects only data from the 10 cities/provinces with the highest transaction volumes: Hanoi, Ho Chi Minh City, Da Nang, Binh Duong, Hai Phong, Dong Nai, Khanh Hoa, Bac Ninh, Long An, and Quang Ninh. The tool also integrated a mechanism to detect and remove duplicate data based on URLs and listing IDs, ensuring each property is stored only once, even if the listing appears under multiple web addresses or categories. We tested several popular data collection libraries to determine the most suitable one for the task. Table I. shows that curl_cffi has the highest efficiency, as it supports the impersonation technique, which enables Chrome browser TLS/HTTP fingerprint simulation to bypass anti-bot mechanisms without launching a headless browser.

Table I: Comparison of web Data Crawling Libraries

Tested Library	Result with batdongsan.com.vn
requests (standard library)	403 Forbidden; immediate block due to TLS fingerprint
urllib3	403 Forbidden - TLS fingerprint issue
Selenium	Functional but slow, approximately 5-10s/request, RAM consumption above 500MB
curl_cffi	Performed well, simulates Chrome fingerprint, approximately 0.5s/request.

From the collected data, only the records of two common property types found on real estate trading platforms in Vietnam are retained: apartments and residential properties. Apartments typically include attributes such as area, number of bedrooms, district, house direction, furniture condition, and legal status. Residential properties often include important attributes such as number of floors, frontage, and road width. Two separate models are trained on the dataset, allowing each model to learn the correct data structure and price relationships specific to each property type.

B. Preprocessing and Data Analysis

i. *Data Cleaning and Standardisation*

First, we removed empty columns, such as the toilets column. Duplicate records were also removed based on the listing_id field.

During collection, some records contained errors where the price and price_per_m2 values were swapped. We automatically detected and corrected these records before further processing.

For the price-per-square-meter attribute, records with the value "Negotiable price" were treated as missing price information and standardised as missing values. Finally, we converted all selling prices to the same unit, billion Vietnamese dong, and removed records without price information.

ii. *Classification and Data Separation by Property Type*

Based on the property_type attribute, the data were classified as follows:

- **Apartments**: Listings where the property type contains the term "apartment" were classified into the *df_chung_cu* data frame.
- **Residential Property**: Listings where the property type contains the terms "private house" or "villa" were classified into the *df_nha_dat* data frame.
- **Unclassified Data**: Records that did not belong to either group (e.g., abnormal values due to incorrect input) were identified as unclassified and removed from the subsequent processing pipeline to ensure model accuracy.

iii. *Data Cleaning for Both Property Types*

- **District**: Districts with fewer than 30 records were grouped into the "Other" category to reduce data sparsity.
- **Number of Bedrooms**: The number of bedrooms was extracted from textual data. Missing values were replaced with the median value of the corresponding district. If the district lacked sufficient data, we used the dataset median.
- **Furniture** (*furniture_std*): Standardized into four groups: Fully Furnished, Basic, Unfurnished, and Unknown.
- Legal status (*legal_std*): Standardized into four groups: Land-use right certificate/house ownership certificate, sale and purchase agreement, pending certificate, and unknown.
- **House and Balcony Direction**: Standardised different direction representations into nine common groups: East, West, South, North, Northeast, Southeast, Northwest, Southwest, and Unknown for missing or unidentified cases.

iv. *Removing Irrelevant Attributes and Inappropriate Records for Apartment Data*

For apartment data, attributes such as number of floors, frontage, and road width are generally not applicable and were removed. Based on market characteristics and transaction practices in Vietnam, we apply an outlier filter to the apartment data. The criteria for each attribute are shown in Table II.

Table II: Criteria for Filtering Outliers for Vietnamese Apartments Data

Feature	Valid Range	Rationale
area_m2 - Area	20 – 300 m^2	Apartments smaller than 20 $m^2$are unrealistic; apartments larger than 300 m^2 are usually penthouses and rare
price_billion – Price	0.3 - 50 billions	Remove abnormally priced listing or ultra-luxury apartments with limited representation.
bedrooms_num - Number of bedrooms	1 - 6 rooms	Normal apartment usually have no more than 6 bedrooms; larger values may indicate unsuitable data.

v. *Handling Missing Data and Removing Irrelevant Attributes*

Attributes with missing values were replaced with the median of all values for that attribute. Some attributes are relevant only to specific property types. Therefore, we excluded irrelevant attributes from the corresponding product type. The feature details are demonstrated in Table III.

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Table III: Feature set Used for Each Property Type

Feature	Meaning	Apartment	Residential Property
Area_m2	Area	Yes	Yes
Bedroom_num	Number of bedrooms	Yes	Yes
City	Province/City	Yes	Yes
District	District	Yes	Yes
Direction	House Direction	Yes	Yes
Furniture_std	Standardize Interior Design	Yes	Yes
Legal_std	Standardise Legal Status	Yes	Yes
Floors_num	Number of floors	No	Yes
Frontage_m	Frontage	No	Yes
Road_width_m	Road Width	No	Yes

After preprocessing, three main data files were constructed: The cleaned_chung_cu.csv and cleaned_nha_dat.csv were used to train and evaluate the Linear Regression, Decision Tree, and Random Forest models. The files were also used as input data for preprocessing the train and test datasets of the Transformer model. The cleaned_full_web.csv was used for search, property detail display, analytics, and similar property recommendations in the Web App. Table IV. shows the descriptive statistics for each product type after data cleaning, based on the files cleaned_chung_cu.csv and cleaned_nha_dat.csv.

Table IV: Statistics After Data Cleaning

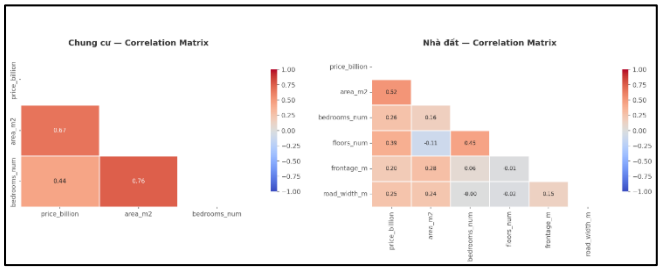
Dataset	Count	Mean	std	Median	Min-Max
Apartment – price_billion	5,452	7.35 billion	6.02 billion	5.50 billion	0.693–50 billion
Apartment – area_m2	5,452	80.61 m²	33.66 m²	73.00 m²	20–300 m²
Residential property – price_billion	6,379	12.61 billion	12.39 billion	8.69 billion	0.545–172 billion
Residential property – area_m2	6,379	71.17 m²	55.02 m²	60.00 m²	15–935 m²
Residential property – frontage_m	6,379	5.05 m	3.48 m	4.50 m	1–200 m
Residential property – floors_num	6,379	3.95 floors	1.60 floors	4.00 floors	1–10 floors

The boxplot in Figure 1. compares the price distributions of apartments and residential properties, together with a Pearson correlation statistics table. The two property types have distinct medians, interquartile ranges, and price ranges, showing that their price distributions differ. Residential properties have higher prices and greater dispersion.



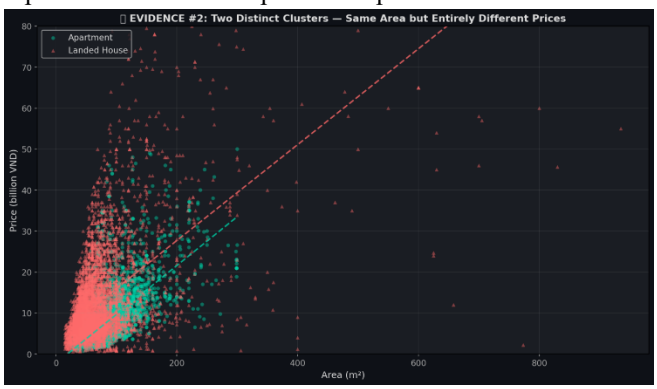
[Fig.1: Boxplot Distribution of Apartment and Residential Properties Price and Pearson Correlation]

The heatmaps in Figure 2. illustrate the correlation structure of the two datasets, which differ significantly. For residential properties, floors_num (r = 0.386) and frontage_m (r = 0.202) correlate notably with price, whereas these features are not present in the apartment dataset. This suggests that different real estate types are affected by different factors and do not share the same price-formation mechanism.



[Fig.2: Correlation Heatmaps. Left: Apartment (Area, r = 0.667). Right: Residential Property (Area, r = 0.520; Floors, r = 0.386)]

The scatterplot in Figure 3. shows two clear clusters on the area-price plane with a distinct trend line. Apartment properties are concentrated in smaller areas with lower prices, while residential properties are more widely dispersed and have a steeper price slope. This suggests that a single model would struggle to fit both trends simultaneously. For the same area, apartment and residential property prices form two separate data clusters, indicating that one rule cannot represent the relationship between price and area.



[Fig.3: Scatterplot Between Area and Price]

The stacked bar chart in Figure 4. illustrates the uneven distribution of listings across districts, as well as the variation in average listing prices between districts. Apartment listings accounted for a substantial proportion of the total listings in most districts. Districts such as District 2, District 7, and District 9 have high listing densities, reflecting strong real estate market development in these areas. Meanwhile, residential properties have significantly fewer and more scattered listings across districts. Accordingly, we group districts with fewer than 30 listings into the 'Other' category to reduce noise and improve data stability. Figure 4. This also shows that average listing prices differ significantly by district, suggesting location is an important feature in house price prediction.

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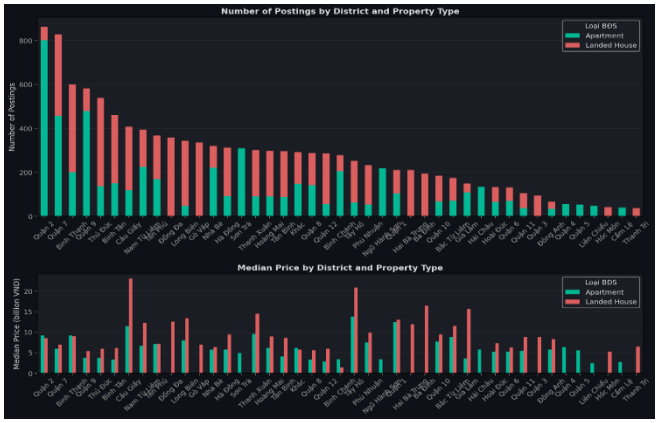

[Fig.4: Listing Distribution and Average Prices by District from 11,831 Cleaned Records]

The EDA charts in Figure 1., Figure 2., Figure 3., and Figure 4. illustrate the significant difference between apartment and residential property data after cleaning. These observations support selecting a multi-model architecture with two separate models, one for apartments and one for residential properties, to better learn each group's characteristics and improve prediction accuracy.

C. Preprocessing Real Estate Data for Transformer Model

Data obtained in Section 2 were preprocessed to suit the Transformer model. The model uses the input variables and the target variable for training. The target variable is the house price, measured in billion Vietnamese doing. The input variables include numerical variables such as area, number of bedrooms, number of floors, frontage, and road width, as well as categorical variables such as district, house direction, furniture condition, legal status, and property type. We standardised and encoded variable values to make them suitable for the model. First, numerical variables were standardised to obtain an embedding vector:

$$Normalized\ value\ = \frac{(x\ -\ \overline{x})}{std}$$

Where $\overline{x}$ is the mean and std is the standard deviation of the training set.

Second, we encoded categorical variables into integer IDs. We used these IDs to look up the corresponding embedding vectors in the embedding matrix. During training, the embedding vector elements were automatically adjusted to better represent each value's characteristics, improving the model's predictive capability. An example of the district column is shown in Table V.

Table V: Example of District Column

Original Value	ID after Encryption	Vector Embedding
Ba Dinh	1	[0.7163, -0.0061, -0.1261, 0.2254, 1.5300, -0.9777, ...]
Cau Giay	6	[0.3539, 0.4813, 1.5311, 1.2479, -0.0701, 1.3733, ...]
…	…	…

III. MODEL DEVELOPMENT AND EVALUATION FOR APARTMENT AND REAL ESTATE PRICE FORECASTING IN VIETNAM

Based on the dataset obtained in Section B, a Transformer model for forecasting real estate prices is built. We trained the Transformer model using the AdamW optimiser, which incorporates decoupled weight decay regularisation to improve parameter optimisation [6]. We evaluated model performance using appropriate metrics and compared it with traditional machine learning methods. The results not only identify the model with the best predictive performance but also provide a foundation for deploying an online real estate price prediction Web App that can support users in referencing and valuing properties based on real-world data.

A. Dataset Splitting

Table VI. describes how the dataset obtained in Section B was split into apartments and residential properties sub-datasets.

Table VI: Dataset Splitting

Dataset	Apartment	Residential Property
Train (80%)	4,361 samples	5,103 samples
Test (20%)	1,091 samples	1,276 samples
Random state	42 – ensuring reproducibility	42 – ensuring reproducibility
Total cleaned samples	5,452 samples	6,379 samples

B. Training and Evaluation of Transformer Model

The model was trained using Mean Squared Error (MSE) loss with the AdamW optimiser [4,9]. At each update, the model predicted real estate prices from the input data and compared the predictions with the actual values to calculate the MSE loss. This loss value was used in backpropagation to compute parameter gradients. AdamW optimiser then updated the model weights to reduce prediction error. During each epoch, the training process was carried out as follows:

- Divide the training set into batches and sequentially feed each batch into the model.
- Predict the real estate prices for each sample in the batch.
- Calculate MSE loss between predicted prices and actual prices.
- Perform backpropagation to compute gradients for the parameters.
- Update model weights using the AdamW optimiser.
- After completing each epoch, evaluate model performance on the validation set.
- If the Validation MSE improves compared with previous epochs, save the corresponding model weights as a checkpoint.
- If the Validation MSE does not improve after a predefined number of consecutive epochs, activate the Early Stopping mechanism to terminate training and reduce the risk of overfitting.

The model was configured with a maximum of 80 training epochs. However, due to the Early Stopping mechanism, training stopped after 25 epochs for the apartment dataset and 26 epochs for the residential property dataset, when validation performance no longer improved significantly. The results show that the model achieved its best performance at epoch 15 for the apartment dataset and epoch 16 for the residential property dataset. We selected the weights from

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these two epochs as the final models for prediction and evaluation on the test set. Table VII. and Table VIII. show the performance evaluation of different models for apartment and residential property datasets.

Table VII: Performance Evaluation of Different Machine Learning Models with Apartment Dataset

Algorithm	Linear Regression	Decision Tree	Random Forest	Transforme r
R2 Test	0.6240	0.5354	0.6608	0.6451
RMSE (billion)	3.3663	3.7421	3.1972	3.1608
MAE (billion)	2.0306	2.0285	1.7132	1.7821
MAPE	33.10%	30.50%	25.20%	26.40%
CV R2 Mean	0.6275 ± 0.0332	0.5726 ± 0.0424	0.6894 ± 0.0288	
Overfit Gap	0.0075	0.3021	0.2366	0.0673

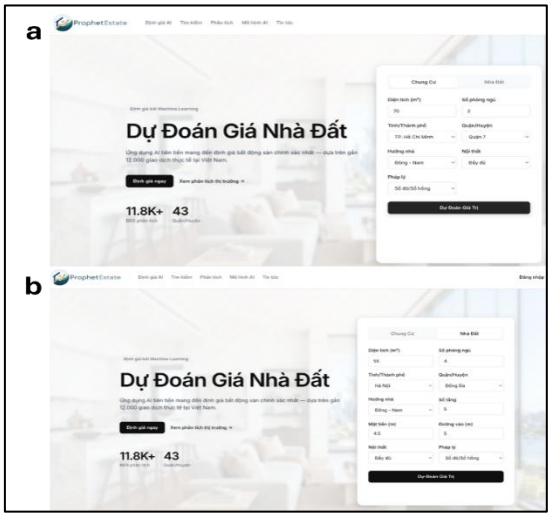
Table VIII: Performance Evaluation of Different Machine Learning Models with the Residential Property Dataset

Algorithm	Linear Regression	Decision Tree	Random Forest	Transformer
R2 Test	0.6123	0.6189	0.7416	0.7355
RMSE (billion)	7.4822	7.4182	6.1078	6.0772
MAE (billion)	4.1900	3.7645	3.0991	3.2697
MAPE	42.10%	33.00%	27.40%	30.30%
CV R2 Mean	0.5836 ± 0.0236	0.5785 ± 0.0327	0.7329 ± 0.0145	
Overfit Gap	-0.0194	0.2752	0.199	0.0944

Table VII. and Table VIII. shows that Transformer consistently ranks among the best-performing models. For the apartment dataset, Transformer achieved the lowest RMSE. For the residential property dataset, Transformer also had the lowest RMSE and a highly competitive R2 compared with the Random Forest model. In addition to high accuracy, Transformer also had a relatively small overfitting gap, suggesting better generalisation than some of the other models.

These results indicate that Transformer not only achieves high predictive accuracy but also remains stable when applied to new data. This demonstrates the model's ability to learn nonlinear relationships and effectively exploit information from multiple input features, making Transformer a suitable model for real estate price prediction in Vietnam within the scope of this study.

Additionally, we integrated the Transformer-based real estate price prediction model for Vietnam into a Web App platform. The user interface of the website Figure 5. was designed to be simple and user-friendly. On the home page, users can access the AI Valuation function to open the real estate price prediction screen.

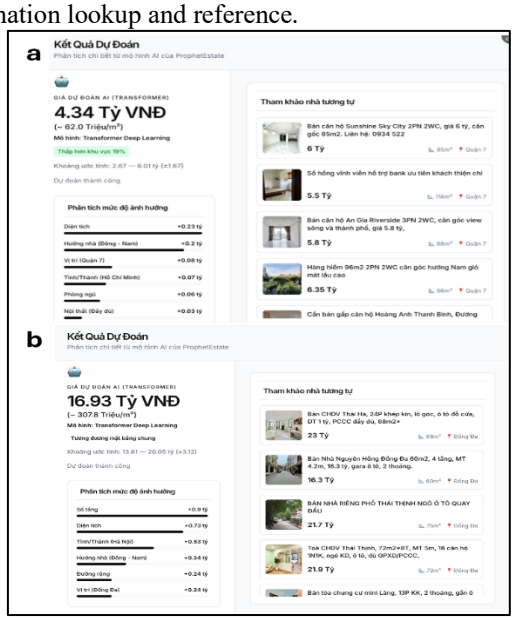


[Fig.5: The user Interface of the Web App. a, When the Mode "Apartment" is selected. b, When Mode "Residential Property" is Selected]

If "Apartment" is selected, the user must enter values for seven attributes: area, number of bedrooms, province/city, district, house direction, and legal status, as shown in Figure 6a. The prediction result is displayed as shown in Figure 6a.

If "Residential property" is selected, the user must enter values for ten attributes, including area, province/city, district, house direction, balcony direction, furniture condition, legal status, number of floors, frontage, and road width as shown in Figure 6b. The prediction result is displayed as shown in Figure 6b.

In addition to apartment and residential property price prediction, the system also recommends properties with similar price levels in the same area, aiding users in comparing alternatives. Experimental results show that the system achieves good prediction accuracy, operates stably, and provides an effective experience for real estate information lookup and reference.



[Fig.6: The Result of Real Estate Price Prediction. a, Apartment Price Prediction. b, Residential Property Price Prediction]

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IV. CONCLUSION

Based on the study of machine learning models applied to real estate price prediction using data collected from a real estate website, this study proposes a data collection, analysis, and preprocessing process to support forecasting real estate prices in selected major provinces and cities in Vietnam. The study compares different machine learning models to select one capable of estimating real estate values close to Vietnamese market prices for the two main product groups: apartments and residential properties. Integrating the model into a web-based system allows users to input real estate information and quickly receive prediction results, supporting price reference, buying and selling decisions, and investment decisions. At the same time, the system provides a foundation for continued data updates and future improvements in model accuracy.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been sponsored or funded by any organization or agency.
- **Ethical Approval and Consent to Participate:** The data provided in this article is exempt from the requirement for ethical approval or participant consent.
- **Data Access Statement and Material Availability:** The data in this article are publicly accessible.
- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals.

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AUTHORS' PROFILE



Dr. Phan Thi Ha is currently a lecturer at the Faculty of Information Technology at Posts and Telecommunications Institute of Technology (PTIT) in Vietnam and at the Computing Fundamental Department, FPT University, Hanoi 10000, Vietnam. She received a B.Sc. in Math & Informatics, an M.Sc. in Mathematical Guarantee for Computer Systems, and a PhD in Information Systems in 1994, 2000, and 2013, respectively. Her research interests include machine learning, natural language processing, and applications of mathematics.



Dr. Tran Thi Thuy Ha is currently a lecturer and a researcher at the Faculty of Electronics Engineering at Posts and Telecommunications Institute of Technology (PTIT) in Vietnam. She received a B.Sc. in Radio-Electronics Engineering in 1998 (Hanoi University of Science, Vietnam National University), an M.Sc. in Radio-Electronics Engineering in 2002 (Faculty of Technology, Vietnam National University) and a PhD in Electronic Engineering in 2021. Her research interests include electronics engineering and microelectromechanical systems (MEMS).

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