Al-Qadisiyah Journal For Engineering Sciences 18 (2025) 360 – 367

Contents lists available at: http://qu.edu.iq

Al-Qadisiyah Journal for Engineering Sciences

Journal homepage: https://qjes.qu.edu.iq

Research Paper

Land price prediction model for housing development in metropolitan area using deep learning technique: A case study of Thailand

Kongkoon Tochaiwat and Anake Suwanchaisakul

Faculty of Architecture and Planning, Thammasat University, Pathum Thani, Thailand.

ARTICLE INFO

Article history:
Received 26 May 2025
Received in revised form 27 July 2025
Accepted 15 October 2025

keyword:
Land valuation
Metropolitan area
Deep learning
Land price influencing factors
Valuation model

ABSTRACT

Thailand has experienced a significant concentration of development in Bangkok, leading to a continual and substantial increase in land prices within the capital city. This phenomenon has driven greater interest among investors in the metropolitan areas surrounding Bangkok, which are less dense but show promising potential for future development. However, investing in these new areas requires extensive knowledge, the experience of professional appraisers, and highly accurate data. Therefore, this research aimed to propose a method for analyzing land value in the Bangkok metropolitan region using Deep Learning technique. The goal was to offer real estate developers a more precise and reliable tool for evaluating appropriate land prices. The research methodology included the collection of vacant land data within Bangkok and its surrounding provinces from feasyonline.com, a credible real estate data source in Thailand. The data was then analyzed using Deep Learning technique, considering 29 independent variables that influence land prices. These variables can be grouped into five key factors, ranked by importance: (1) type of business in the area, (2) infrastructure, utilities, and community services, (3) specific physical characteristics of the land, (4) legal and regulatory constraints, and (5) location-related factors. The model developed in this study demonstrated high performance, with a Coefficient of Determination (R^2) of 0.71 and a Root Mean Square Error (RMSE) of 6,068.08—both considered acceptable values and better than those of the application's Auto Model. The research findings can be applied in two main ways. First, in a business context, investors and developers can use the model to support decision-making when acquiring lands for new projects, designing project types, and determining appropriate selling prices. Second, in academic development, researchers and interested individuals can adapt the Deep Learning technique for studies involving real estate business analysis with limited data, or customize the database, project types, or incorporate additional variables into the model.

1. Introduction

Bangkok, the capital city of Thailand, serves as the country's center of development. As a result, it has a high population density, leading to increasingly elevated land values [1, 2]. In response to rising land prices, an alternative for real estate developers and investors is to consider land located in the metropolitan area, comprising five provinces adjacent to Bangkok: Nakhon Pathom, Samut Sakhon, Nonthaburi, Pathum Thani, and Samut Prakan. Each area exhibits a different rate of growth [3]. According to the Real Estate Information Center (REIC) in the first quarter of 2024, when compared to the same quarter of the previous year, the top three areas with the highest land value growth rates were as follows: Nakhon Pathom showed a change rate of 89.4%, the area of Mueang Samut Prakan–Phra Pradaeng–Phra Samut Chedi had a price change rate of 13.9%, and Samut Sakhon recorded a price change rate of 12.4%. These figures reflect the impact of urban expansion on rising land prices in suburban areas. Land value plays a crucial role in determining the cost and selling price of residential real estate projects [4] and is a key component in the cost structure that developers analyze to ensure the projected profitability of their projects. However, accurate land valuation requires reliable data, and relying solely on market comparison methods can lead to deviations from the appropriate pricing [5, 6]. In this study, the researcher designed a methodology involving the collection of land value data from feasyonline.com, a credible real estate data source in Thailand, for various areas within the metropolitan provinces. The study then analyzed the factors influencing land value using Deep Learning technique, a type of Machine Learning known for its high accuracy and precision with capabilities to learn from both numerical data and image data [7, 8]. While previous studies have commonly employed regression techniques, which are effective in numerical data analysis, this research recognizes the presence of many influential variables, including complex physical characteristics that are not easily represented by numerical values. To address this complexity, the researchers selected Deep Learning as the analytical approach. This technique not only handles large datasets but is also well-suited for analyzing intricate, non-linear, and high-dimensional data. By identifying this research gap, the study adopted Deep Learning to develop a predictive model for land valuation. The model's accuracy and precision were evaluated and improved until reaching an acceptable performance level. The resulting model can serve as an effective decision-making tool for property developers, landowners, and brokers in determining fair and appropriate land transaction prices.

* *Corresponding Author.*
E-mail address: anake_s@tu.ac.th ; Tel: (+66) 089 810-1803 (Anake Suwanchaisakul)

https://doi.org/10.30772/qjes.2025.160749.1571
2411-7773

Nomenclature

ANN	Artificial Neural Network	*MLR*	Minimum Lending Rate
AREA	Agency for Real Estate Affairs (Thai Comany)	*R*	Pearson's Correlation Coefficient
BMA	Bangkok Metropolitan Administration	*REIC*	Real Estate Information Center (Thai Institute)
GIS	Geographic Information System	*RMSE*	Root Meand Square Error

2. Literature review

2.1 Internal land factors

The internal land factors refer to the characteristics inherent to the land itself that directly affect its value. Based on several studies and research performed by The Treasury Department, Chetsadawan [9], Asavaphanthip [10], Srisomboon [11], Abdulla et al [12] and Gao & Asami [13], several key insights emerge. The plot size should be appropriate for its intended use. for example, larger plots for agricultural purposes, and medium- to small-sized plots for the development of residential properties such as single-detached houses or condominiums. In terms of land shape, square or rectangular plots offer greater efficiency in land utilization compared to irregularly shaped plots. Frontage width, or the length of the land that faces a road, also plays a role in determining land value. Greater frontage width provides more flexibility and fewer limitations for project access points [14]. The natural condition of the land, including elevation and original features such as depressions or water retention areas, influences its value as well. For instance, if the land surface is higher than the adjoining road, it generally holds a higher value since lower-elevation land may require additional investment for landfilling during development [15, 16]. Beyond physical characteristics, legal constraints on land use also significantly affect land value. In Thailand, land parcels are subject to varying legal regulations. Land with fewer regulatory constraints is more desirable. The examples of regulatory constraints include land-use maps and building height regulations [9, 17–19] and other development restrictions. Residential developments such as single-detached houses, semi-detached houses, and townhouses are commonly permitted. In addition, land with higher value is typically complied well with legal requirements for commercial development [14].

2.2 External land factors

External land factors refer to the conditions beyond the land's inherent characteristics that influence its increasing value. For instance, land located near shopping mall developments provides greater convenience for consumer activities compared to land situated far from such amenities. The presence and accessibility of community facilities, such as market, retail store, public park, club, and sports complex, can significantly impact land value depending on their availability and ease of use [20–23]. A good location is a critical factor in determining land value. In Thailand's metropolitan fringe areas, or Greater Bangkok, accessibility to urban infrastructure is lower, competition is less intense, and lifestyles, particularly in terms of transportation, differ from those in the capital. Land close to city centers or populated communities, located within municipal zones or local administrative organizations, and near major transportation routes generally commands a higher value. According to numerous studies such as those by Subongkotch [14], The Treasury Department, Chetsadawan [9], BMA's Department of City Planning [24], Guntawilai [25], He [26], Maris [27], Li [28], Lin [29], Lopez-Morales [30], Wang et al [31], Malaitham et al [32], Colwell & Munneke [33] and Yang et al [34], location is a key determinant of land value. The factors include the distance from central business districts or community centers and the quality and convenience of surrounding land-use areas. Literature review revealed the key location-based factors affecting land value as follows: Distance from the city center or community hub: The closer a property is to the urban core, the higher its value [35, 36]. Municipal zoning: Land located within municipal boundaries or under local government jurisdictions tends to benefit from better access to infrastructure, public utilities, and government services [14]. In addition, the local economic structures surrounding the land reflect the potential or growth trends of the area. These include factors such as population expansion, road development, improvements in public utilities and infrastructure, and investment in housing or other real estate projects from the private sector [9, 10, 27, 37]. Furthermore, the research works performed by Kim et al. [38], Lake et al. [39], Liang [40], Nakamura [41], Asavaphanthip [10], Yuan [42], and Nicholls [43] highlights the importance of the physical environment surrounding land. Environmental conditions, e.g., cleanliness, wind direction, temperature, odor, noise, lighting, water sources, greenery, and overall scenic value, can directly impact land value. For instance, the presence of open space in the land has a positive effect on land value [44]. Air quality affects the long-term livability of an area and may be influenced by nearby land uses, such as environmental pollution resulting from areas with excessive population density and growth [45] and industrial zones [46]. Noise pollution from highways and expressways [47], as well as traffic congestion [48], also contribute to fluctuations in land value.

2.3 Transportation and accessibility factors

Transportation in the metropolitan areas differs from that in the capital city. With lower traffic density, commuting by car is generally more convenient. Factors influencing transportation in these metropolitan areas include the distance from roads and transportation routes, such as highway, primary road, secondary road, and access road [28, 49–52]. In addition to the proximity to major road, the condition of the road passing through or near the land is also considered. Relevant factors include road type whether it is a highway, primary road, secondary road, alley, or small lane and road width, which determines the number of lanes and traffic capacity. The road surface material, such as concrete, asphalt, gravel, or dirt, is also important [18, 49, 53]. These transportation factors directly affect the convenience and accessibility of essential destinations such as workplaces, public utilities, government offices, markets, shopping centers, banks, schools, universities, hospitals, religious sites, highway entrances/exits, and other key facilities [14, 18, 36, 51, 54–56]. Additionally, accessibility to major areas, such as tourist attractions via pedestrian routes [22], or areas with high pedestrian traffic through the land [57]. This is because the areas that allow safe and comfortable pedestrian movement reflect public space with good environmental conditions [58–61] and can further enhance the land's value. Conversely, land plots with limited access or difficulty in reaching external areas will experience a decrease in value.

2.4 Summary of factors

From literature review, it can be observed that the three categories of factors are interrelated and contributed to the potential increase in land value. Therefore, these aforementioned factors can be categorized into different themes for further analysis during data collection, as detailed in Table 1.

Table 1. Factors and subfactors used in the research.

Factor	Subfactor	Authors
Location	1) External land factor 2) Transportation and accessibility factors.	[?, 9, 12, 14, 18, 22, 24–36, 49–55, 62–64]
Site characteristic	1) Internal land lactors	[?, 9–13, 16, 17, 50]
Infrastructure facilities and community services	1) External land factors 2) Transportation and accessibility factors	[9–11, 19, 21, 23, 37, 42, 49, 55, 56, 65–67]
Surrounding physical environment	1) External land factors	[10, 38, 39, 41–45]
The local economy	1) External land factors	[9, 10, 27, 37, 68, 69]
Legal regulations	1) Internal land factors	[7, 11, 14–16, 34, 45]

2.5 Deep learning

Deep Learning is a technique that builds upon Artificial Neural Networks (ANN), which is a subset of Machine Learning. Deep Learning simulates the neural network structure in the human brain [70], which consists of multiple layers. These layers include the first layer (Input Layer), the middle layer (Hidden Layer), and the final layer (Output Layer) [71]. This process enables computers to learn and make predictions from data by recognizing patterns and classifying data for analysis and forecasting. Currently, businesses at the national level choose to use Deep Learning technique because of their high accuracy and efficiency. The role of Deep Learning has been applied in various fields, such as marketing for personalized customer service management, the development of voice and emotion recognition systems for customer communication, and its use in finance to save time, reduce costs, and increase value. For example, computers can be used to assess the creditworthiness of loan applicants in banks [72]. It has also applied in the healthcare field. However, Deep Learning has some limitations. It requires data labelling or classification, as it still relies on human supervision (supervised learning) and requires large datasets to train the models. For example, creating an effective classification model may need many data samples, and up to one million samples may be

Table 2. Variables used in the research.

Factor	Subfactor	Issue	Variable name
Location	1. External land factors 2. Transportation and accessibility factors.	1. Distant from Location to city center. 2. Location is in the municipality. 3. Distance to main roads. 4. Road surface conditions, road conditions. 5. There are various public transportation systems.	Location
Site characteristic	Internal land factors	1. Size of the land plot 2. Shape of the land 3. Geography of the land 4. Height of the land 5. Width of the land on the side that faces the road	Land Shape Land Area Land Width Land Depth
Infrastructure facilities and community services	1. External Land Factors 2. Transportation and accessibility factors internal land factors	1. Various public utilities such as water, electricity, telephone systems 2. Various public utilities such as markets, shops, parks, etc.	Distance from Public Road, Road Width Distance from Intersect Road or Bridge Foot Distance to Intersection or Road or Flyover Retail, Market, Education, Hospital, Public Transport
Surrounding physical environment	External land factors	The physical environment of the land location, such as air temperature, smell, noise	Temperature, Factory Nearby Dirty Area, Construction area
The local economy	External land factors	The type of economy in each area affects the value of that area	Shop House, Apartment, Single Building, Warehouse Temple, Housing, Gas Station, Farm
Legal regulations	Internal land factors	Land color schemes, land use laws affect the value of the land	Corner road, Obstacles, Colour Code Amount of Public Road, River Width

Table 3. Variables in the factors used to collect data.

Row	Variable name	Meaning	Variable weight	Level of measurement
01	Location	Location in Metropolitan Area	0.011	Nominal
02	Land Shape	Shape of land	0.063	Nominal
03	Land Area	Land area in Square Wa unit	0.066	Interval
04	Land Width	Land frontage width	0.091	Interval
05	Land Depth	Land depth	0.121	Interval
06	Distant	Distant from public road	0.033	Interval
07	Road Width	Width of the road in front of Land	0.088	Interval
08	Distance	Distance from roads to junction, intersection or bridge ramp near the land	0.063	Interval
09	Distance Type	Type of road near the land, whether it's a shared road, an intersection, or a bridge.	0.000	Nominal
10	Corner (road)	The number of roads adjacent to the land makes the land a corner plot.	0.030	Interval
11	Obstacles	Land obstacles such as high-voltage electric poles	0.063	Nominal
12	Color Code	Color code	0.052	Nominal
13	Public road	Number of public roads next to land	0.053	Interval
14	River Width	The width of the public river	0.017	Interval
15	Shophouse	The adjacent land area used for shophouse.	0.230	Ratio
16	Apartment	The adjacent land area used for apartments.	0.045	Ratio
17	Single Building	The adjacent land area used for single building	0.054	Ratio
18	Warehouse	The adjacent land area used for warehouse	0.047	Ratio
19	Temple	The adjacent land area used for temple.	0.025	Ratio
20	Housing	The adjacent land area used for housing.	0.008	Ratio
21	Gas Station	Utilization of adjacent land as Gas station	0.019	Ratio
22	Farm	Utilization of adjacent land as farmland	0.131	Ratio
23	Retail	The distance from a retail is not more than 1 kilometer	0.054	Ratio
24	Market	The distance from a market is not more than 1 kilometer	0.068	Ratio
25	Education	The distance from school or college is not more than 1 kilometer	0.106	Ratio
26	Hospital	The distance from a hospital is not more than 1 kilometer	0.211	Ratio
27	Transportation	The distance from a express train station is not more than 1 kilometer	0.165	Ratio
28	Treasury	Prices set by the Treasury Department	0.703	Interval
29	Market	Land market price	Variables used for prediction (Label)	Interval

needed to achieve results that are close to human-level performance. Additionally, Deep Learning can be complex when explaining results, which makes it difficult to accept. Deep Learning technique mimics the functioning of Artificial Neural Networks (ANN) by increasing the number of stacked hidden layers, as shown in Fig. 1, resulting in more accurate outcomes. However, the challenge lies in identifying a suitable neural network architecture and determining the variables that influence the performance of the network during training [65]. The more complex the processing layers, the deeper the structure becomes, leading to more intricate results. For example, a neural network with four hidden layers can process more complex data than a network with only two layers.

3. Research methodology

3.1 Data source

This research employed a quantitative approach, utilizing Deep Learning technique. The model necessitates data for computer training, referred to as input data. The data collection site is an open-source platform. Most land value listings are dispersed across various online platforms and presented in different formats. To ensure consistency and reliability, this study selected Feasyonline, a platform known for having the largest land value database in Thailand. Specifically, the website www.feasyonline.com, which hosts a database from the Agency for Real Estate Affairs [AREA], which is widely used in Thailand, as shown in Fig. 2. This figure illustrates the annual growth of land prices in various zones, with the geographical scope limited to the Metropolitan area including Nakhon Pathom, Nonthaburi, Pathum Thani, Samut Prakan, and Samut Sakhon, as shown in Fig. 3.

3.2 Research process

From a comprehensive literature review, this research categorized the collected data into groups, representing various factors influencing land prices, such as Site Characteristics and Local Economy data. After data collecting, a land price forecasting model for the Metropolitan area was developed using RapidMiner program, which offers comparable accuracy and reduced processing time compared to Python [66]. The data analysis in RapidMiner involved setting the target variable (land market price) as 'Label'. The remaining data were then divided into two parts: First part was used to train the computer to understand which factors influence the differences in land prices and which components contribute to a piece of land being of higher or lower value. Out of the total of 187 land data entries, 168 entries (90%) were used for training. Once the computer learned from the entire training dataset, the second part of data is the remaining 10%, or 18 land data entries, were used for prediction to test the computer's accuracy. The model's performance was then evaluated using the R^2 (Coefficient of Determination) and RMSE (Root Mean Square Error) values. After that, an Auto Model automatically developed by RapidMiner was used to automatically adjust the parameters and generate a model to compare with the previously developed one.

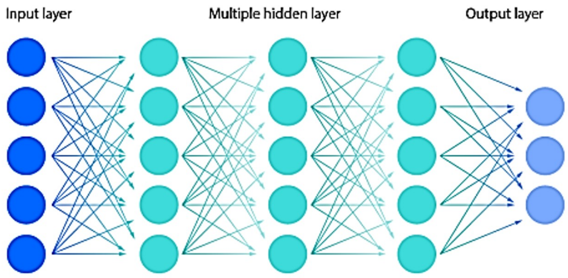

Figure 1. Deep Learning structure, [67].

Figure 2. Data of land advertised for sale.

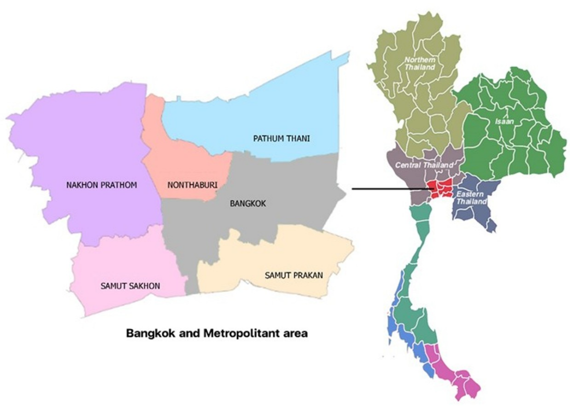

Figure 3. Map of bangkok metropolitan region.

Table 4. Parameter adjustments in Deep Learning model.

Model Number	Hidden Layers	Activation Function	R^2	RMSE
01	25:12:0	Quadratic	0.372	090,982.40
02	26:11:0	Quadratic	0.416	087,988.10
03	27:10:0	Quadratic	0.385	089,855.10
04	28:09:0	Quadratic	0.409	088,816.70
05	24:13:0	Quadratic	0.392	089,500.26
06	15:12:0	Quadratic	0.293	096,193.93
07	16:11:0	Quadratic	0.461	084,299.35
08	17:10:0	Quadratic	0.475	082,762.83
09	18:09:0	Quadratic	0.499	081,630.00
10	14:10:3	Quadratic	0.346	092,978.09
11	50:25:0	Quadratic	0.612	073,760.41
12	51:26:0	Quadratic	0.626	069,803.53
13	52:27:0	Quadratic	0.605	071,695.45
14	49:26:0	Quadratic	0.691	063,468.96
15	49:27:0	Quadratic	0.712	006,068.08
16	28:06:3	Quadratic	0.323	093,972.53
17	28:05:4	Quadratic	0.446	085,138.83
18	24:10:3	Quadratic	0.429	087,207.88
19	15:09:3	Quadratic	0.275	097,902.38
20	16:08:3	Quadratic	0.378	090,559.33
21	17:07:3	Quadratic	0.323	094,029.56
22	25:12:0	Huber	0.124	107,468.00
23	26:11:0	Huber	0.132	106,661.80
24	27:10:0	Huber	0.165	104,746.10
25	28:09:0	Huber	0.097	109,049.00
26	24:13:0	Huber	0.060	111,160.96
27	15:12:0	Huber	0.010	114,142.43
28	16:11:0	Huber	0.073	118,790.91
29	17:10:0	Huber	0.166	105,065.00
30	14:10:3	Huber	0.065	110,905.19
31	14:09:4	Huber	0.154	105,448.13
32	25:09:3	Huber	0.049	111,906.36
33	26:08:3	Huber	0.122	107,563.11
34	27:07:3	Huber	0.013	113,590.96
35	28:06:4	Huber	0.190	103,000.00
36	28:06:3	Huber	0.120	107,174.83
37	28:05:4	Huber	0.022	113,284.00
38	24:10:3	Huber	0.153	105,601.00
39	15:09:3	Huber	0.066	111,020.00
40	16:08:3	Huber	0.048	111,899.00
41	17:07:3	Huber	0.117	107,658.51
42	25:12:0	Absolute	0.206	102,344.56
43	26:11:0	Absolute	0.203	102,154.53
44	27:10:0	Absolute	0.386	090,113.96
45	28:09:0	Absolute	0.329	094,526.56
46	24:13:0	Absolute	0.268	098,477.40
47	15:12:0	Absolute	0.255	098,719.71
48	16:11:0	Absolute	0.273	097,638.58
49	17:10:0	Absolute	0.232	100,601.76
50	14:10:3	Absolute	0.015	114,036.15
51	14:09:4	Absolute	0.239	100,470.63
52	25:09:3	Absolute	0.196	102,769.30
53	26:08:3	Absolute	0.254	099,266.50
54	27:07:3	Absolute	0.281	096,797.00
55	28:06:4	Absolute	0.253	098,995.00
56	28:06:3	Absolute	0.232	100,137.00
57	28:05:4	Absolute	0.263	098,399.00
58	24:10:3	Absolute	0.226	100,728.00
59	15:09:3	Absolute	0.318	095,256.25
60	16:08:3	Absolute	0.219	101,433.29
61	17:07:3	Absolute	0.287	097,019.64
62	25:12:0	Quantile	0.344	093,036.00
63	26:11:0	Quantile	0.341	093,057.73
64	27:10:0	Quantile	0.302	095,816.00
65	28:09:0	Quantile	0.253	099,235.00
66	24:13:0	Quantile	0.312	094,759.00
67	15:12:0	Quantile	0.242	099,611.00
68	16:11:0	Quantile	0.179	104,411.66
69	17:10:0	Quantile	0.328	094,092.43
70	14:10:3	Quantile	0.275	097,465.82

4. Results

4.1 Related variables

The researchers defined a total of 31 variables obtained from the literature review, which were organized into categories, and compared them with the database that can be collected through the feasyonline.com website, as shown in Table 2.

4.2 Model development process

As shown in Table 2, a total of 31 variables were initially identified through literature review and data available from the website feasyonline.com. However, the variables under the category of physical environmental conditions could not be obtained from online databases and were considered varied to time. As a result, the total number of usable variables was reduced to 29 while the Variable No.29 Market Price was the target variable used for predicting the market price of the land. In this research, the data collection was limited to vacant land within Bangkok Metropolitan. A total of 187 land plots met the criteria of having complete data, accurate listing locations, and verifiable positions via geographical Information System (GIS) applications such as Google Maps and Landsmaps, the application developed by Thailand's Department of Lands. After testing and comparing the alternative 60 different models with varying formats and parameters using the RapidMiner software, the model with the lowest RMSE included 29 input variables, with the market price serving as the target variable, as presented in Table 3.

4.3 Results of the land value forecasting model

After the data were prepared for analysis 28 variables (input data) that influence land value were used to create a predictive model for land value in residential development areas within Bangkok. The analysis was conducted using a Deep Learning technique by adjusting the parameters through the RapidMiner program. The objective was to achieve the lowest possible RMSE value with an R^2 value within an acceptable range. In the Deep Learning based land price prediction process, the market price variable was assigned as the prediction target (Label), and the parameters, i.e., hidden layer configuration and the type of activation function, were adjusted across 81 iterations, as shown in Table 4. The results indicated that the most effective model was achieved when the hidden layers were configured at a ratio of 49:27, using a quadratic activation function (Model 15 in Table 4). This configuration yielded an R^2 value of 0.710 and an RMSE of 6,068.08, indicated that the model demonstrates a good predictive performance. Furthermore, the performance of the acquired Deep Learning model was compared with the automated Deep Learning model (Auto Model) generated by RapidMiner. The Auto Model produced a considerably higher RMSE of 82,056.48 and a lower R^2 value of 0.633. Therefore, it can be concluded that the acquired model is generally considered acceptable to strong in real estate forecasting contexts, where data tends to be complex and influenced by multiple interacting factors.

5. Analysis of research results

The model input data shows the factors that affect the land price (Market Price) in descending order of weight as follows:

1. Prices Set by the Treasury Department (0.703)
2. Utilization of Adjacent Land as Shophouses (0.23)
3. Distance from the Hospital is Less Than 1 Kilometer (0.211)
4. Distance from Public Transport is Less Than 1 Kilometer (0.165)
5. Utilization of Adjacent Land as Farmland (0.131)
6. Land Depth (0.121)
7. Distance from Education Place is less than 1 Kilometer (0.106)
8. Land Width (0.091)
9. Width of the Road in Front of Land (0.088)
10. Distance from Market Place is Less Than 1 Kilometer (0.068)
11. Land Area (0.066)
12. Land Shape (0.063)
13. Distance from Roads That are Junctions, Intersections or Bridge Ramps Near the Land (0.063)
14. Land Obstacles such as High-voltage Electric Poles (0.063)
15. Distance from Retail place is Less Than 1 Kilometer (0.054)
16. Utilization of Adjacent Land as Single Building (0.054)
17. Amount of Public Road Near Land (0.053)
18. Color Code (0.052)
19. Utilization of Adjacent Land as Warehouse (0.047)
20. Utilization of Adjacent Land as Apartment (0.045)
21. Distance From Public Roads (0.033)v Roads Adjacent to the Land that Make the Land Have the Characteristics of Corner Plot (0.030)v Utilization of Adjacent Land as Temple (0.025)
22. Utilization of Adjacent Land as Gas Station (0.019)
23. Width of the River Next to Land (0.017)
24. Location (0.011)
25. Utilization of Adjacent Land as Housing Residence (0.008)
26. Characteristics of the Road Near the Land, Whether It Is a Junction, Intersection or Bridge Ramp (0.004).

After examining the weights of the factors influencing land prices, it was found that the factor groups affecting land value, ranked from highest to lowest impact, are as follows: 1) The Local Economy; 2) Infrastructure Facilities and Community Services; 3) Site Characteristic; 4) Legal Regulations; 5) Location. Among the individual factors, the appraised land price announced by the Treasury Department held the highest weight, indicating consistency between the official appraised land values in the Bangkok metropolitan area and the actual market prices. However, it is important to note that the Treasury Department's land prices are primarily intended for calculating transaction-related fees and differ from market prices, which reflect the real economic value of land [73, 74]. A comparison with related studies revealed that distance-related variables can significantly impact land value. For instance, the distance from land to public roads, public utilities, and transportation infrastructure such as transit stations or electric railway systems has been shown to influence land value [32]. The Deep Learning model proved to be a suitable approach for land price prediction and analysis [75–78]. Although Deep Learning techniques are generally well-suited for large datasets, this study demonstrated that the technique can still perform effectively even with a relatively small dataset, such as when appraising land values. This finding is consistent with the work of Morano et al. [79] and Tochaiwat et al. [80], who indicated that Deep Learning can be applied even when data availability is limited. Nonetheless, the model's accuracy is somewhat limited due to the small dataset. Despite this limitation, the resulting model is sufficiently reliable to support project development analysis. This aligns with the perspectives of Ozili [81], who noted that the R^2 value depends heavily on the nature of the research. Studies aiming to predict human behavior or preferences—which typically involve numerous and less-structured variables—often yield lower R^2 values compared to research in more structured scientific domains.In this study, the resulting R^2 value was 0.710, indicating a relatively strong explanatory power in predicting land prices based on the selected input features. This result demonstrates notable predictive accuracy when compared to traditional statistical models, particularly multiple linear regression (MLR). Based on the literature review, it was found that the R^2 values of Multiple Linear Regression (MLR) vary depending on the degree of linear relationships among the variables. When the relationships between variables are nonlinear, MLR tends to produce very low R^2 values. For example, Doğan et al. (2025) [82] employed MLR to predict agricultural land prices in Çanakkale, Turkey, and found the model to be inadequate, yielding a significantly low R^2 of only 0.010. In contrast, Sampathkumar et al. (2015) [83] applied MLR to forecast land prices in the Chennai metropolitan area and reported a high R^2 of approximately 0.963. Furthermore, the R^2 value obtained in this study is also comparable to those reported in other studies that employed Multiple Linear Regression (MLR) for forecasting in real estate-related businesses. The findings of this study are consistent with previous research, such as that of Wassaeng [84], who predicted the sale price of foreclosed single-detached houses and achieved an R^2 value of 0.537; Sitthikankun [85] who conducted research on construction cost estimation for government buildings using linear regression, achieving an R^2 of 0.732; and Viswanatha [86] whose study on predicting used car prices using machine learning reported an R^2 of 0.829.

6. Conclusion and recommendations

This study aims to determine the weight coefficients of variables influencing land value, thereby supporting more efficient land valuation analysis. The findings contribute to resource optimization, as traditional valuation processes typically require on-site inspections, which are time-consuming and labor-intensive. By utilizing the variable outputs from this research, developers can make more informed decisions regarding the suitability of a given plot of land for a specific project, ultimately reducing errors in appropriate price determination. Based on the forecasting model employing Deep Learning techniques, the findings suggested that in the fringe areas of the Bangkok Metropolitan Region, the most significant factor influencing land value is the local economic pattern. Although developers and consumers are often drawn to these peripheral zones due to relatively lower land costs compared to the city center, there is a prevailing expectation of future appreciation in land value. Legal construction constraints were assigned relatively low weight in the model, likely due to the lower population density in these fringe areas, which allows for greater flexibility in land development and consequently fewer regulatory limitations compared to central urban zones. Interestingly, the resulting weight coefficients deviate from the conventional understanding that location is the most critical factor in land valuation—an assumption widely accepted in the context of real estate appraisal within central Bangkok. This research revealed that, in the metropolitan fringe, other variables such as local economic dynamics may exert a greater influence. In addition, the weightings of other contributing factors also differ from traditional valuation frameworks. These findings suggest that, despite the metropolitan fringe areas being geographically adjacent to Bangkok, differences in physical characteristics, population density, and lifestyle-related factors significantly affect land valuation outcomes, making them distinct from those observed in the urban core. These findings align with the former studies that location, physical characteristics, legal regulations, and available amenities influence land value. The Deep Learning model demonstrated sufficient accuracy and efficiency to be used in project feasibility assessments. This is consistent with previous studies by Subongkot [14], Wassaeng [84], Sitthikankun [85], and Viswanatha [86]. The research identifies the potential beneficiaries of these findings. Real estate developers can use the acquired land value prediction model to support feasibility studies, including location selection, project design, and pricing strategies. For researchers and academics, this study provides further evidence supporting the application of Deep Learning techniques to analyze limited sized real estate datasets [79, 80]. It also highlights key factors that influence land value, offering a basis for further studies. This research is subject to several limitations. Firstly, the dataset was exclusively obtained from the website feasyonline.com. Relying on a single data source may limit the comprehensiveness and generalizability of the model. Although incorporating data from multiple online platforms could enhance coverage, it may also introduce challenges such as data duplication and inconsistencies. Additionally, the model was evaluated using a simple data-splitting method, in which the dataset was divided into training and testing sets. This approach, while common, may not fully capture the model's robustness across different scenarios. More advanced validation techniques, such as k-fold cross-validation, could further improve the reliability of the model's performance assessment. Secondly, variables pertaining to physical environmental characteristics were excluded from the model due to their unavailability in existing online databases and their inherent variability over time. Although this limitation may be acceptable with the context of land valuation during the preliminary information-gathering phase prior to on-site inspections, it should be noted that these factors influence the appropriate pricing of land and should be further inspected. In addition, future studies may also consider incorporating additional factors that could influence land value, such as air cleanliness, flood risk, seismic activity, or other environmental hazards. Including such variables would offer a more holistic understanding of land valuation dynamics. Finally, future research could address these limitations by incorporating more diverse and comprehensive datasets, applying the model to various types of real estate development projects. The model could also be refined for application across different geographic regions or evaluated through comparative analyses with other studies to enhance its generalizability and practical utility.

Authors' contribution

All authors contributed equally to the preparation of this article.

Declaration of competing interest

The authors declare no conflicts of interest.

Funding source

This study was supported by Thammasat University Research Fund, Contract No. TDS l6/2566.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgements

The authors would like to acknowledge the Faculty of Architecture and Planning, Thammasat University.

References

[1] "Real estate information center (REIC). vacant land price index before development in Bangkok and Metropolitan area in quarter 4," 2023. [Online]. Available: https://www.reic.or.th/Activities/PressRelease/165

[2] M. Aziz and B. Ghafour, "Evaluation of residential density of single-family housing in Erbil housing/investment projects," *Al-Qadisiyah Journal for Engineering Sciences*, vol. 17, no. 1, pp. 58–65, 2024. [Online]. Available: https://doi.org/10.30772/qjes.2023.142139.1014

[3] K. Tochaiwat, A. Budda, and P. Seniwong, "Forecasting technologies impacting real estate business during the transition to 2030s," *Al-Qadisiyah Journal for Engineering Sciences*, vol. 18, no. 1, pp. 92–98, 2025. [Online]. Available: https://doi.org/10.30772/qjes.2025.155895.1450

[4] K. Tochaiwat, "Innovative real estate development," *Government Housing Bank Journal*, vol. 22, pp. 67–76, 06 2016. [Online]. Available: https://www.researchgate.net/publication/304462250_Innovative_Real_Estate_Development

[5] M. Ball, C. Lizieri, and B. MacGregor, *The Economics of Commercial Property Markets*, ser. Economics, urban studies. Routledge, 1998. [Online]. Available: https://books.google.iq/books?id=8qGZCtQQYvYC

[6] N. Dunse, C. Jones, and M. White, "Valuation accuracy and spatial variations in the efficiency of the property market," *Journal of European Real Estate Research*, vol. 3, no. 1, pp. 24–45, 2010. [Online]. Available: https://doi.org/10.1108/17539261011040523

[7] Y. Bengio, I. Goodfellow, and A. Courville, "Deep learning," *Cambridge, MA, USA: MIT press*, vol. 1, pp. 23–24, 2017. [Online]. Available: http://www.deeplearningbook.org

[8] S. Almabdy and L. Elrefaei, "Deep convolutional neural network-based approaches for face recognition," *Applied Sciences*, vol. 9, no. 20, 2019. [Online]. Available: https://www.mdpi.com/2076-3417/9/20/4397

[9] C. Chetsadawan, "Property valuation standards guidelines (Nonthaburi)," *Construction and Building Materials*, vol. 46, pp. 8–12, 2005.

[10] M. Sharkawy and S. Chotipanich, "Housing segmentation in developing countries in transition: A recent case study of residential development in Bangkok," *Journal of Real Estate Literature*, vol. 6, pp. 29–42, 1998. [Online]. Available: https://doi.org/10.1023/A:1008658229939

[11] F. Collins, J. Lambert, and W. H. Duan, "The influences of admixtures on the dispersion, workability, and strength of carbon nanotube–opc paste mixtures," *Cement and Concrete Composites*, vol. 34, no. 2, pp. 201–207, 2012. [Online]. Available: https://doi.org/10.1016/j.cemconcomp.2011.09.013

[12] M. Abdulla, A. Ibrahim, and S. Al-Hinkawi, "The impact of urban street network on land value: Correlate syntactical premises to the land price," *Buildings*, vol. 13, no. 7, p. 1610, 2023. [Online]. Available: https://doi.org/10.3390/buildings13071610

[13] X. Gao and Y. Asami, "Effect of urban landscapes on land prices in two japanese cities," *Landsacpe and Urban Planning*, vol. 81, no. 1-2, pp. 155–166, 2007. [Online]. Available: https://doi.org/10.1016/j.landurbplan.2006.11.007

[14] P. Subongkotch, "Factors affecting the land appraisal in Angthong province. thesis master degree of economics," *School of Economics, Sukhothai Thammathirat Open University*, 2019.

[15] Y. Xiao, E. C. Hui, and H. Wen, "Effects of floor level and landscape proximity on housing price: A hedonic analysis in Hangzhou, China," *Habitat International*, vol. 87, pp. 11–26, 2019.

[16] F. Zakaria and A. Fatine, F., "Towards the hedonic modelling and determinants of real estates price in Morocco," *Social Sciences Humanities Open*, vol. 4, no. 1, p. 100176, 2021. [Online]. Available: https://doi.org/10.1016/j.ssaho.2021.100176

[17] K. Nakajima and K. Takano, "Estimating the effect of land use regulation on land price: At the kink point of building height limits in Fukuoka," *Regional Science and Urban Economics*, vol. 103, may 2023.

[18] Q. C. Doan, "Determining the optimal land valuation model: A case study of Hanoi, Vietnam," *Land Use Policy Elsevier*, vol. 127, no. c, p. 106578, 2023. [Online]. Available: https://doi.org/10.1016/j.landusepol.2023.106578

[19] J. C. S. V. . S. N. Ruksasri, A., "Factors influencing land price assessment in Chatuchak district, Bangkok," *Maejo Business Review*, vol. 4, no. 2, 2022.

[20] F. Lan, Q. Wu, T. Zhou, and H. Da, "Spatial effects of public service facilities accessibility on housing prices: A case study of Xi'an, China,"

Sustainability, vol. 10, no. 12, p. 4503, 2018. [Online]. Available: https://doi.org/10.3390/su10124503

[21] S. Qu, S. Hu, W. Li, C. Zhang, Q. Li, and H. Wang, "Temporal variation in the effects of impact factors on residential land prices," *Applied Geography*, vol. 114, no. 1, p. 102124, 2020. [Online]. Available: https://doi.org/10.1016/j.apgeog.2019.102124

[22] L. Yang, B. Wang, J. Zhou, and X. Wang, "Walking accessibility and property prices," *Transportation Research Part D: Transport and Environment*, vol. 62, no. 2018, pp. 551–562, July 2018. [Online]. Available: https://doi.org/10.1016/j.trd.2018.04.001

[23] L. Zhang, J. Zhou, and E. Hui, C.M., "Which types of shopping malls affect housing prices? from the perspective of spatial accessibility," *Habitat International*, vol. 96, p. 102118, 2020. [Online]. Available: https://doi.org/10.1016/j.habitatint.2020.102118

[24] "Department of city planning and urban development (bma). principles of land adjustment techniques for land value and rearranging land plots," *BMA*, no. 5, pp. 32–44, 2006.

[25] B. Guntawilai, "Evaluation of state property land value of number 1723 by hedonic pricing method, Tambon Donkaew, Mae Rim, Chiang Mai. thesis," *The Faculty of Economics, Chiang Mai University*, p. 39, 2017. [Online]. Available: https://cmudc.library.cmu.ac.th/frontend/Info/item/dc:124418

[26] S. Y. He, "Regional impact of rail network accessibility on residential property price: Modelling spatial heterogeneous capitalization effects in Hong Kong," *Transportation Research Part A. Policy and Practice, Elsevier*, vol. 135, no. c, pp. 244–263, 2020. [Online]. Available: https://doi.org/10.1016/j.tra.2020.01.025

[27] M. M, "The importance of location factors in determining land prices: The evidence from bratislava's Hinterland," *REGION*, vol. 8, no. 1, pp. 181–198, 2021. [Online]. Available: https://doi.org/10.18335/region.v8i1.328

[28] J. Li and H. Huang, "Effects of transit-oriented development (tod) on housing prices: A case study in Wuhan, China," *Research in Transportation Economics (Elsevier)*, vol. 80, no. c, p. 100813, 2020. [Online]. Available: https://doi.org/10.1016/j.retrec.2020.100813

[29] X. Lin, B. Niu, W. Liu, J. Zhong, and Q. Dou, "Land premium effects of urban rail transit and the associated policy insights for tod: A case of Ningbo, China," *Urban rail transit*, vol. 8, no. 3-4, pp. 157–166, 2022. [Online]. Available: https://doi.org/10.1007/s40864-022-00180-z

[30] E. Lopez-Morales, C. Sanhueza, N. Herrera, S. Espinoza, and V. Mosso, "Land and housing price increases due to metro effect: An empirical analysis of Santiago, Chile, 2008-2019," *Land Use Policy*, vol. 132, no. 10387, p. 102118, 2023. [Online]. Available: https://doi.org/10.1016/j.landusepol.2023.106793

[31] Y. Wang, H. Ruan, and C. Tian, "Access to high-speed rail and land prices in China's Peripheral regions," *Cities*, vol. 130, no. 2, p. 103877, 2022. [Online]. Available: https://doi.org/10.1016/j.cities.2022.103877

[32] S. Malaitham, A. Fukuda, V. Vichiensan, and V. Wasuntarasook, "Hedonic pricing model of assessed and market land values: A case study in Bangkok Metropolitan area, Thailand," *Case Studies on Transport Policy*, vol. 8, no. 1, pp. 153–162, 2020. [Online]. Available: https://doi.org/10.1016/j.cstp.2018.09.008

[33] F. Colwell and H. Munneke, J., "Land prices and land assembly in the CBD," *The Journal of Real Estate Finance and Economics*, vol. 18, no. 1, pp. 163–180, 1999. [Online]. Available: https://doi.org/10.1023/A:1007714624700

[34] L. Yang, K. Chau, W. Szeto, X. Cui, and X. Wang, "Accessibility to transit, by transit, and property prices: Spatially varying relationships," *Transportation Research Part D: Transport and Environment*, vol. 85, no. 1, p. 102387, 2020. [Online]. Available: https://doi.org/10.1016/j.trd.2020.102387

[35] Z. Li, "The impact of metro accessibility on residential property values: An empirical analysis," *Research in Transportation Economics*, vol. 70, no. c, pp. 52–56, 2018. [Online]. Available: https://doi.org/10.1016/j.retrec.2018.07.006

[36] R. Rakhmatulloh, I. Buchori, W. Pradoto, and B. Riyanto, "The power of accessibility to land price in Semarang urban corridors, Indonesia," *Journalof the Malaysian Institute of Planners*, vol. 16, no. 1, pp. 118–129, 2018. [Online]. Available: https://doi.org/10.21837/pm.v16i5.416

[37] C. Sun, C. Sun, Z. Yang, and Y. Deng, "Urban land development for industrial and commercial use: A case study of Beijing," *Sustainability (Multidisciplinary Digital Publishing Institute)*, vol. 8, no. 12, p. 1323, 2016. [Online]. Available: https://doi.org/10.3390/su8121323

[38] S. Kim, J. Park, and Y. Kweon, "Highway traffic noise effects on land price in an urban area," *Transportation Research Part D: Transport and Environment*, vol. 12, no. 4, pp. 275–280, 2007. [Online]. Available: https://doi.org/10.1016/j.trd.2007.03.002

[39] R. Lake, A. Lovett, I. Bateman, and I. Langford, H., "Modelling environmental influences on property prices in an urban environment," *Computers, Environment and Urban Systems*, vol. 22, no. 2, pp. 121–136, 1998. [Online]. Available: https://doi.org/10.1016/S0198-9715(98)00012-X

[40] C. Liang, "The impact of air pollution on urban land price and willingness to pay for clean air – evidence from micro level land transactions in China," *Journal of Cleaner Production*, vol. 414, no. 15, p. 137790, 2023. [Online]. Available: https://doi.org/10.1016/j.jclepro.2023.137790

[41] H. Nakamura, "Relationship among land price, entrepreneurship, the environment, economics, and social factors in the value assessment of Japanese cities," *Journal of Cleaner Production*, vol. 217, pp. 144–152, 2019. [Online]. Available: https://doi.org/10.1016/j.jclepro.2019.01.201

[42] F. Yuan, Y. Wei, and J. Wu, "Amenity effects of urban facilities on housing prices in China: Accessibility, scarcity, and urban spaces," *Cities*, no. 4, p. 102433, 2020. [Online]. Available: https://doi.org/10.1016/j.cities.2019.102433

[43] S. Nicholls, "Impacts of environmental disturbances on housing prices: A review of the hedonic pricing literature," *Journal of Environmental Management*, vol. 246, pp. 1–10, 2019. [Online]. Available: https://doi.org/10.1016/j.jenvman.2019.05.144

[44] M. Aziz and S. Ahmed, "Post occupancy evaluation of private open spaces in dwelling units in single family investment housing projects in Erbil city," *Al-Qadisiyah Journal for Engineering Sciences*, vol. 17, no. 2, pp. 97–103, 2024. [Online]. Available: https://doi.org/10.30772/qjes.2023.141738.1011

[45] O. Jassima and Z. D. Abbasl, "Application of gis and ahp technologies to support of selecting a suitable site for wastewater sewage plant in Al-Kufa city," *Al-Qadisiyah Journal for Engineering Sciences*, vol. 12, no. 1, pp. 31–37, 2019. [Online]. Available: https://doi.org/10.30772/qjes.v12i1.586

[46] A. e. a. Mar Iman, "The effects of environmental disamenities on house prices," *Malaysian Journal of Real Estate*, vol. 4, no. 2, 2009.

[47] A. Zambrano-Monserrate and M. Ruano, A., "Does environmental noise affect housing rental prices in developing countries? evidence from ecuador," *Land Use Policy*, vol. 87, no. 1, p. 104059, 2019. [Online]. Available: https://doi.org/10.1016/j.landusepol.2019.104059

[48] H. Wen, Z. Gui, L. Zhang, and E. Hui, "An empirical study of the impact of vehicular traffic and floor level on property price," *Habitat International*, vol. 97, p. 102132, 2020. [Online]. Available: https://doi.org/10.1016/j.habitatint.2020.102132

[49] A. Phaophoo, "The impact of the mass transit transporation development on land values alongside the extended mrta green line (bareing-samutprakarn). independent study, master degree of ART program in business economics," *Thammasat University*, 2015.

[50] W. Likitanupark and S. Techarojanapakin, "Prediction model for eastern bangkok land price," *Veridian E-Journal Silpakorn University*, vol. 12, no. 4, pp. 1425–1435, 2020.

[51] L. Yang, J. Zhou, F. Shyr, and D. Huo, "Does bus accessibility affect property prices?" *Cities*, vol. 84, pp. 56–65, 2019. [Online]. Available: https://doi.org/10.1016/j.cities.2018.07.005

[52] C. Mulley, C. Tsai, and L. Ma, "Does residential property price benefit from light rail in Sydney?" *Research in Transportation Economics*, vol. 67, no. C, pp. 3–10, 2018. [Online]. Available: https://doi.org/10.1016/j.retrec.2016.11.002

[53] T. Al-Mansoori, N. Al-Mukaram, and A. Shubbar, "GIS technology for enhancing pavement maintenance and condition assessment: Case study," *Al-Qadisiyah Journal for Engineering Sciences*, vol. 18, no. 1, pp. 78–82, 2025. [Online]. Available: https://doi.org/10.30772/qjes.2024.150276.1256

[54] C. Tian, T. Peng, W. Wen., Yue, and L. Fang, "Subway boosts housing values, for whom: A quasi-experimental analysis," *Research in Transportation Economics*, vol. 90, no. C, p. 100844, 2021. [Online]. Available: https://doi.org/10.1016/j.retrec.2020.100844

[55] E. Zolnik, "Geographically weighted regression models of residential property transactions: Walkability and value uplift," *Journal of*

Transport Geography, vol. 92, p. 103029, 2021. [Online]. Available: https://doi.org/10.1016/j.jtrangeo.2021.103029

[56] L. Somantri, "Land price mapping in the northern suburbs of Bandung city west java province Indonesia," *Forum Geografi*, vol. 34, no. 1, pp. 26–40, 2020. [Online]. Available: https://doi.org/10.23917/forgeo.v34i1.10412

[57] B. Humphreys and X. Feng, "Assessing the economic impact of sports facilities on residential property values: A spatial hedonic approach," *Journal of Sports Economics*, vol. 19, no. 2, 2008. [Online]. Available: https://doi.org/10.1177/1527002515622318

[58] A. Sara Israt and A. S. Hassan, "A comparative analysis of assessing the quality of the urban pedestrian environment in Dhaka using syntactic and statistical methods," *Al-Qadisiyah Journal for Engineering Sciences*, vol. 18, no. 1, pp. 1–9, 2025. [Online]. Available: https://doi.org/10.30772/qjes.2024.153021.1369

[59] Y. Wang, D. Potoglou, S. Orford, and Y. Gong, "Bus stop, property price and land value tax: A multilevel hedonic analysis with quantile calibration," *Land Use Policy*, vol. 42, pp. 381–391, 2015. [Online]. Available: https://doi.org/10.1016/j.landusepol.2014.07.017

[60] M. Ahlfeldt and G. Kavetsos, "Form or function?: The effect of new sports stadia on property prices in London," *Journal of the Royal Statistical Society*, vol. 177, no. 1, pp. 169–190, 2014. [Online]. Available: https://doi.org/10.1111/rssa.12006

[61] W. Jin, C. Zhou, and L. Luo, "Impact of land input on economic growth at different stages of development in Chinese cities and regions," *Sustainability*, vol. 10, no. 8, 2018. [Online]. Available: https://doi.org/10.3390/su10082847

[62] S. Y. He., "Regional impact of rail network accessibility on residential property price: Modelling spatial heterogeneous capitalization effects in Hong Kong," *Transportation Research Part A :Policy and Practice*, vol. 135, no. C, pp. 244–263, 2020. [Online]. Available: https://doi.org/10.1016/j.tra.2020.01.025

[63] R. Cordera, P. Coppola, L. dell'Olio, and A. Ibeas, "The impact of accessibility by public transport on real estate values: A comparison between the cities of Rome and Santander," *Transportation Research Part A: Policy and Practice*, vol. 125, no. 1, pp. 308–319, 2019. [Online]. Available: https://doi.org/10.1016/j.tra.2018.07.015

[64] C. Lee, "The relationship between foot traffic and commercial land prices," *GEOGRAFIE*, vol. 129, no. 1, pp. 1–13, 2024. [Online]. Available: https://doi.org/10.37040/geografie.2024.005

[65] K. Tochaiwat and P. Seniwong, "Sales rate prediction for condominiums in the Bangkok Metropolitan region using deep learning: Identification of determinants and model validation," *Nakhara Journal of Environmental Design and Planning*, vol. 24(, no. 1, p. 502, 2025. [Online]. Available: https://doi.org/10.54028/NJ202524502

[66] K. Laszlo and H. Ghous, "Efficiency comparison of python and rapidminer," *Multidiszciplináris Tudományok*, vol. 10, no. 3, p. 212–220, 2020. [Online]. Available: https://doi.org/10.35925/j.multi.2020.3.26

[67] IBM and D. A. Team, "Ai vs. machine learning vs. deep learning vs. neural networks: What's the difference?" *IBM*, 2023. [Online]. Available: https://www.ibm.com

[68] Y. Wu, X. Zhang, M. Skitmore, Y. Song, E. Hui, and C.M., "Industrial land price and its impact on urban growth: A Chinese case study," *Land use Policy*, vol. 36, no. 1, pp. 199–209, 2014. [Online]. Available: https://doi.org/10.1016/j.landusepol.2013.08.015

[69] M. Song, Q. Xie, and J. Chen, "Effects of government competition on land prices under opening up conditions: A case study of the Huaihe river ecological economic belt," *Land Use Policy*, vol. 113, no. C, p. 105875, 2022. [Online]. Available: https://doi.org/10.1016/j.landusepol.2021.105875

[70] T. Shakir Khuzan and M. A. Al-Jumailib, "Analysis of rural road traffic crashes in Al-Diwaniyah province using artificial neural network," *Al-Qadisiyah Journal for Engineering Sciences*, vol. 15, no. 4, pp. 224–228, 2022. [Online]. Available: https://doi.org/10.30772/qjes.v15i4.856

[71] IBM, "What is a neural network?" 2021. [Online]. Available: https://www.ibm.com/think/topics/neural-networks

[72] J. D. Kelleher, "Deep learning," *MIT press.*, 2019. [Online]. Available: https://doi.org/10.7551/mitpress/11171.001.0001

[73] Feasyonline, "What is the difference between land price, market price, appraisal price, and purchase price?" 2020. [Online]. Available: https://www.feasyonline.com

[74] GHBank., "What is the difference between the selling price of land and the appraisal price? what do you need to know before setting a price?" *Hampshire, U.K*, vol. 96, p. 102118, 2024. [Online]. Available: https://blog.ghbank.co.th

[75] J. R. Rico-Juan and P. T. de La Paz, "Machine learning with explainability or spatial hedonics tools? an analysis of the asking prices in the housing market in Alicante, Spain," *Expert Systems with Applications*, vol. 171, p. 114590, 2021. [Online]. Available: https://doi.org/10.1016/j.eswa.2021.114590

[76] B. Afonso, L. Melo, W. Oliveira, S. Sousa, and L. Berton, "Housing prices prediction with a deep learning and random forest ensemble," *Anais Do XVI Encontro Nacional de Inteligência Artificial e Computacional (ENIAC 2019)*, vol. 16, p. 389–400, 2019. [Online]. Available: https://doi.org/10.5753/eniac.2019.9300

[77] N. Nghiep and C. Al, "Predicting housing value: A comparison of multiple regression analysis and artificial neural networks," *Journal of Real Estate Research*, vol. 22, no. 3, p. 313–336, 2001. [Online]. Available: https://doi.org/10.1080/10835547.2001.12091068

[78] N. Zainun, I. Rahman, and M. Eftekhari, "Forecasting low-cost housing demand in johor bahru, malaysia using artificial neural networks (ANN)," *Journal of Mathematics Research*, vol. 2, no. 1, pp. 14–19, 2010. [Online]. Available: https://doi.org/10.5539/jmr.v2n1p14

[79] P. Morano, F. Tajani, and C. M. Torre, "Artificial intelligence in property valuations. an application of artificial neural networks to housing appraisal," *In book:Advances in Environmental Science and Energy Planning,*, p. 23–29, 2015. [Online]. Available: https://api.semanticscholar.org/CorpusID:42318396

[80] K. Tochaiwat, P. Seniwong, and D. Rinchumphu, "Sales rate forecasting of single-detached houses using artificial neural network technique," *Decision Making: Applications in Management and Engineering*, vol. 6, no. 2, pp. 772–786, 2023. [Online]. Available: https://doi.org/10.31181/dmame622023707

[81] P. K. Ozili, "The acceptable r-square in empirical modelling for social science research," *Social Research Methodology and Publishing Results, SSRN*, 2022. [Online]. Available: http://dx.doi.org/10.2139/ssrn.4128165

[82] S. Dogan, L. Genc, S. Yucebas, and M. Usaklı, "Analyzing agricultural land price prediction using linear regression and XGBoost machine learning algorithms: a case study of Çanakkale," *Turkish Journal of Agriculture-Food Science and Technology*, vol. 13, no. 5, p. 1109–1116, 2025. [Online]. Available: https://doi.org/10.24925/turjaf.v13i5.1109-1116.7379

[83] V. Sampathkumar, M. Santhi, and J. Vanjinathan, "Forecasting the land price using statistical and neural network software," *Procedia Computer Science*, vol. 57, p. 112–121, 2015. [Online]. Available: https://doi.org/10.1016/j.procs.2015.07.377

[84] P. Wassaeng and K. Tochaiwat, "Forecasting the selling prices of non-performing asset detached housesin Bangkok by machine learning techniques," *Journal of Educational Innovation and Research*, vol. 8, no. 1, p. 423–439, 2004. [Online]. Available: https://doi.org/10.14456/jeir.2024.26

[85] S. Sitthikorn, C. Buachat, and D. Rinchumphu, "Construction cost estimation for government building using artificial neural network techniques." *International Transaction Journal of Engineering, Management, and Applied Sciences and Technologies*, vol. 12, no. 6, pp. 1–12, 2021. [Online]. Available: https://doi.org/10.14456/ITJEMAST.2021.112

[86] Y. Zhu, "Prediction of the price of used cars based on machine learning algorithms," *Applied and Computational Engineering*, vol. 6, pp. 671–677, 2023. [Online]. Available: https://doi.org/10.54254/2755-2721/6/20230917

How to cite this article:
Kongkoon Tochaiwat and Anake Suwanchaisakul. (2025). 'Land price prediction model for housing development in metropolitan area using deep learning technique: A case study of Thailand', Al-Qadisiyah Journal for Engineering Sciences, 18(4), pp. 360-367. `https://doi.org/10.30772/qjes.2025.160749.1571`