

Forecasting Real Estate Prices and Rents Using LSTM Algorithms

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Abstract

Predictive modelling constitutes a fundamental component in the utilization of data by organizations for decision-making purposes. When firms employ this methodology, they can anticipate future occurrences, discern emerging trends, mitigate risks, and optimize resource utilization. The real estate market significantly influences the economy, impacting consumer spending patterns, construction activity, and housing availability. Obtaining precise estimates of the costs associated with flats and rentals is crucial to financial planning and policy-making. The autonomous learning capabilities of machine learning have emerged as a pivotal element in the proliferation of automation. Likewise, it plays a vital role as a valuable tool in data analysis and a source of inspiration for individuals with artistic inclinations. In this recent study, we utilized a specific dataset to assess the effectiveness of a classifier in distinguishing between long-term and short-term memory. The conducted investigations revealed a significant correlation of 99% between the elements under investigation and a notable % accuracy rate of 72%. Line plots, heat maps, and bar graphs are illustrative visualizations that can effectively reveal concealed patterns and trends within a dataset.

Keyword: Flat price prediction · Machine learning · LSTM.

1. Introduction

The real estate market is a sector characterized by constant

evolution and dynamism, is susceptible to regular changes, and holds significant economic importance on a global scale[1]. Both individual property owners and investors have a substantial stake in accurately predicting future property values and rental trends. The projections above possess the capacity to offer significant insights that can be employed to make pivotal judgements, including those about real estate transactions such as property acquisition, sale, or rental, as well as decisions that can influence investment strategy[2]. Over the past few years, the academic discipline of machine learning has developed into a powerful tool capable of enhancing predictive capabilities in diverse domains. This advancement has occurred in the past few years. The real estate domain is among the various disciplines and is also subsumed within this overarching classification. Recently, there has been significant interest in long-short-term memory (LSTM) networks within machine learning algorithms[3]. This interest stems from their ability to efficiently capture and interpret the inherent temporal correlations seen in sequential data. This phenomenon can be attributed to the capability of LSTM networks to do both of these tasks. The LSTM-based predictive modelling technique is highly suitable for researching the residential real estate market. It is due to the inherent time-series characteristics of the real estate market, which render it an ideal subject for such an investigation[4]. The variability in property prices and rental rates can be attributed to various underlying factors. These factors encompass economic conditions, changes in population demographics, the advancement of urbanization, and unforeseen events such as pandemics[5][6].

Traditional statistical methodologies are widely recognized for their inherent complexity, leading to frequent challenges encountered during implementation. Successfully capturing the intricacy and non-linear connections inherent in these data streams is a challenging task. The Long Short-Term Memory (LSTM) algorithms, belonging to the category of recurrent neural networks (RNN), demonstrate remarkable proficiency in handling sequential data and display a notable ability in tasks related to time series forecasting[7]. Microsoft Research initially created the Long Short-Term Memory

(LSTM) algorithms and debuted in 2010. The development of the Long Short-Term Memory (LSTM) algorithm family can be attributed to IBM[7]. This research paper examines the application of predictive modelling in the real estate market, specifically focusing on two key components: price prediction and rent forecasting. This research study examines the correlation between predictive modelling and the real estate market. This study aims to demonstrate the effectiveness of long-short-term memory (LSTM) algorithms in capturing and utilizing the underlying temporal patterns seen in real estate data. The study will specifically concentrate on real estate data gathered within the United States' geographical boundaries. This particular target's attainment constitutes the present investigation's fundamental aim. This undertaking offers essential perspectives and resources to aid individuals in making informed judgements. The individuals encompassed by this group consist of homeowners, property investors, real estate professionals, and lawmakers, among several other stakeholders. After exposing the preceding segments of this research endeavour, a thorough examination of the existing literature about the anticipation of real estate markets will be undertaken.

Furthermore, this paper will explain the LSTM technique. Subsequently, the dataset will be visualized, followed by elucidating the implemented preparation activities. Moreover, this paper will include a detailed account of the experimental configuration and a comprehensive examination of the findings. This project aims to enhance comprehension and utilization of machine learning methodologies in real estate market forecasting. The successful culmination of this project will result in the provision of substantial resources to stakeholders within this pivotal industry[8][9].

In preparation for the study's upcoming phases, highlighting key structural elements is imperative. Section 2 will meticulously dissect the literature review, delving into greater depth to comprehensively understand the existing body of knowledge. Moving on to Section 3, the study paper will break down in detail the method behind the study suggested system, giving a clear picture of how it is built

and how it works. Subsequently, Section 4 will be dedicated to thoroughly discussing the results obtained from the study research endeavours. Finally, Section 5 will serve as a culmination, providing readers with a concise summary of the study findings and offering valuable suggestions for future research directions.

2. Literature Review

The real estate industry plays a crucial role in the global economy, as property is a precious asset for individuals and a key catalyst for economic activity[10]. Accurate forecasting of real estate prices and rental rates is paramount for many stakeholders, including homeowners, investors, legislators, and professionals in the real estate industry. This literature review aims to present a comprehensive analysis of the existing body of research on predictive modelling in the context of real estate markets, with a specific emphasis on forecasting prices and rents. Predictive modelling in real estate has undergone substantial advancements during its development[11][12]. Historically, early methodologies essentially utilized fundamental statistical techniques such as time-series analysis and linear regression models. Although these methodologies provide inherent value due to their simplicity, it is essential to acknowledge their limits in effectively capturing the intricate dynamics of the real estate industry. The advent of enhanced computational capabilities and the widespread accessibility of extensive datasets have precipitated a paradigm shift in predictive modelling for the real estate industry. Machine learning techniques, such as random forests, support vector machines, and neural networks, have become increasingly prominent due to their ability to manage extensive and intricate datasets effectively. These methodologies can capture complex, non-linear correlations and complicated patterns inherent in the dataset, leading to more precise and reliable predictions. A crucial aspect of real estate predictive modelling is carefully selecting and effectively utilizing pertinent data sources and attributes. The significance of integrating several data types in research has been emphasized. These data types encompass specific properties-related attributes, such as size, location, and amenities.

Economic indicators, such as GDP growth, inflation, and interest rates, are also considered. Furthermore, demographic information, including population trends and income levels, is also considered. The significance of geospatial data in real estate modelling has witnessed a notable rise[13]. Geographic Information Systems (GIS) facilitate the integration of location-specific attributes, such as proximity to educational institutions, transit infrastructure, commercial establishments, and crime statistics, into research endeavours[14]. By including a spatial perspective, the precision of price and rent predictions is improved as it considers the influence of neighbourhood attributes. The price forecasting process in the real estate sector is characterized by its complexity, mostly stemming from the multitude of elements that influence property values[15][16].

In summary, significant progress has been made in predictive modelling for real estate markets, explicitly concerning the forecasting of prices and rents. The discipline is transitioning from conventional statistical methods to advanced machine learning algorithms while incorporating a wide range of data sources. Nevertheless, there are still obstacles that need to be addressed. These obstacles encompass the uncertain and unforeseeable occurrences of external events, the ethical concerns regarding impartiality and prejudice in prediction algorithms, and the necessity for models that are both visible and capable of being comprehended. With the continuous advancement of technology and the increasing availability of data, it is anticipated that the precision of real estate forecasts will continue to enhance, thereby offering significant and vital knowledge for homeowners, investors, and policymakers. Future research should persist in tackling these issues and endeavour to achieve responsible, ethical, and precise predictive modelling in the constantly evolving real estate market[17].

3. Methodology

Predictive modelling in real estate markets is of utmost importance in research, as it seeks to offer valuable insights into forecasting property prices and rental rates. The primary objective of this study is to explore the use of LSTM (long

short-term memory) algorithms to attain precise predictions. Initially, it is imperative to deconstruct the process into fundamental stages and principles. The initial step involves the creation of a dataset. The whole basis of any predictive modelling study relies on creating a well-structured dataset. In this case, researchers construct the dataset using a response form that collects numerous properties-related attributes. The qualities mentioned earlier encompass dimensions, proximity to significant landmarks, elevation within the building, property age, orientation, flat price, and local flat rental rates. The study gathered an estimated 2000 datasets utilizing this answer form. The datasets used in this study function as the primary data source for the predictive model, with each dataset corresponding to a distinct property listing. The provided text showcases a representative dataset, as depicted in Table 1.

Table 1

1	size	distance	floor	age	facing	flat_price	flat_rent
2	870	1.50	1	2	1	2300000	9000
3	900	2.40	2	5	1	3000000	12000
4	1050	2.00	2	10	2	5000000	15000
5	950	3.00	3	20	3	1700000	7000
6	750	2.00	1	7	4	2700000	10000
7	1000	3.40	4	9	1	2500000	8000
8	1120	2.00	3	5	2	2100000	6000
9	980	1.00	5	15	1	3500000	12000
10	840	3.00	2	3	4	3000000	10000
11	860	1.60	4	4	3	5500000	16000
12	550	4.00	2	10	1	1500000	7000
13	860	2.00	3	5	2	3500000	9000
14	750	1.00	6	4	1	2000000	10000
15	940	4.00	1	8	1	4200000	11000
16	1000	3.00	4	9	2	5000000	12000
17	1240	4.00	8	14	3	5800000	18000
18	680	5.00	10	16	4	2600000	8000
19	780	1.00	6	8	1	3200000	8000
20	500	2.00	1	12	4	1600000	8000
21	640	3.00	2	20	4	2300000	7000
22	840	4.00	4	22	1	2500000	7000
23	960	2.00	3	8	2	3600000	10000
24	970	3.00	7	10	1	3800000	9000
25	930	1.00	9	4	3	3300000	10000
26	850	4.00	10	30	1	2800000	6000
27	750	2.00	5	25	3	2200000	6000

After completing the data preprocessing process, we proceed with additional steps. Before we enter the modelling phase, we subject all the collected responses to a thorough process of filtering and preprocessing. Executing this stage holds utmost importance, as it plays a crucial role in cleansing the data, eliminating any discrepancies, and ensuring its suitability for training the model. Preprocessing involves handling missing

data, encoding categorical variables, and scaling numerical characteristics. Following the data preprocessing steps, we split the dataset into two distinct subsets, a training set and a testing set, to assess the effectiveness of the LSTM-based predictive model. The common practice is to allocate 70% of the data for training purposes while reserving the remaining 30% for testing. The training data serves as the input for the LSTM model, enabling it to acquire knowledge about patterns and correlations inherent in the data. Ultimately, we pass the training data through the LSTM model. Long-short-term memory (LSTM) neural networks exhibit strong compatibility with sequential data and time series forecasting, making them suitable for predicting real estate market trends. These models can effectively capture and incorporate long-range dependencies in the data, a crucial aspect when analyzing and predicting the dynamic nature of real estate market movements. Equations (i) through (vi) present the mathematical formulations for long-short-term memory (LSTM).

$$\begin{aligned}
 i_t &= \sigma(w_i [h_{t-1}, x_t] + b_i) \longrightarrow \text{i} \\
 f_t &= \sigma(w_f [h_{t-1}, x_t] + b_f) \longrightarrow \text{ii} \\
 O_t &= \sigma(w_o [h_{t-1}, x_t] + b_o) \longrightarrow \text{iii} \\
 C_t &= \tanh(w_c [h_{t-1}, x_t] + b_c) \longrightarrow \text{iv} \\
 C_t &= f_t * C_{t-1} * i_t * C'_t \longrightarrow \text{v} \\
 h_t &= O_t * \tanh(C_t) \longrightarrow \text{vi}
 \end{aligned}$$

The equations presented above depict the fundamental structure and functionalities of the Long Short-Term Memory (LSTM) model. These equations encompass the forget gate, input gate, cell state, and output gate, collectively facilitating the model's ability to process and acquire knowledge from sequential inputs effectively. The proposed approach utilizes performance metrics to evaluate its precision and efficacy. It employs several performance indicators to assess the suggested predictive model, including precision, recall, F1 score, R2 score, and mean squared error (MSE).

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) \rightarrow \text{vii}$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN}) \rightarrow \text{viii}$$

$$\text{F1} = 2 (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \rightarrow \text{ix}$$

$$\text{R2} = 1 - \text{SSres} / \text{SStot} \rightarrow \text{x}$$

$$\text{MSE} = \frac{\sum (y_i - \hat{y}_i)^2}{n} \rightarrow \text{xi}$$

Equations vii to xi represent the mathematical expressions for all these performance metrics. The study emphasizes visualization and evaluation, going beyond numerical measurements and incorporating visualizations to comprehensively understand the model's performance. Heatmaps are valuable for visually representing the relationship between several qualities and the target variable. The AUC curve, the Area Under the Curve, is a commonly used metric for evaluating a model's discriminatory power in distinguishing between positive and negative examples. Log loss and accuracy curves offer additional perspectives on the model's performance.

In summary, this research utilizes long-short-term memory (LSTM) algorithms to conduct predictive modelling of real estate markets. The study employs a meticulously constructed dataset derived from a response form. The dataset has been carefully preprocessed, partitioned into separate training and testing sets, and subsequently employed to train the LSTM model. Subsequently, a range of performance indicators and visualizations are employed to assess the accuracy and efficacy of the model in forecasting property values and rental rates. The present study can offer significant contributions to understanding the dynamic and constantly evolving real estate market, thereby assisting investors, buyers, and sellers in making well-informed decisions. Figure 1 shows the methodology diagram.

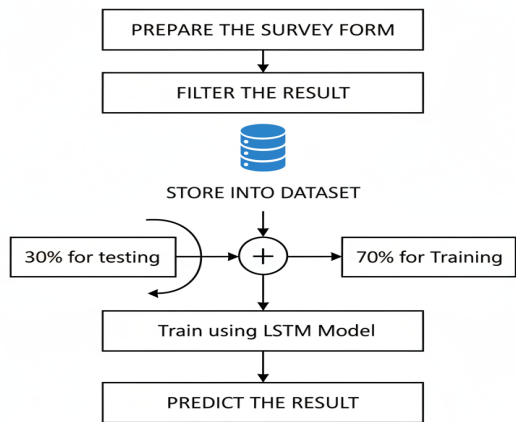


Figure 1: Methodology diagram

4. Result

Table 2: LSTM Performance Matrix

Parameter	Accuracy
Decision Tree Classifier:	72%
F1 Score:	Micro: 72%
	Macro: 57%
Recall Score:	Micro: 72%
	Macro: 60%
Precision Score:	Micro: 72%
	Macro: 57%
R2 Score:	99%
Mean Square Error:	0.132500000010
Mean Absolute Error:	0.52500
Root Mean Square Error:	115108.64433221339

The findings fully assess a machine-learning model using an LSTM classifier trained on a given dataset. The obtained results encompass several metrics and visual representations

that provide insights into the functioning of the model and its comprehension of the data. Firstly, it is noteworthy to mention that the accuracy of the model, which is a crucial statistic in classification tasks, is commendably high at 72%. It indicates that it successfully predicted the class labels for 72% of the samples in the test dataset, showcasing a satisfactory classification ability. Furthermore, the F1 score, a crucial metric considering accuracy and recall, will be discussed. The micro F1 score demonstrates a notable performance of 72%, offering valuable insights into the overall usefulness of the model. Nevertheless, the macro F1 score, which computes the mean of F1 scores across all classes, exhibits a slightly diminished value of 57%. It implies that the model's efficacy may be less reliable for minority classes, necessitating additional examination and potential enhancements in addressing these classes. The recall scores at the micro and macro levels provide additional insight into the model's performance. The microscale score is 72%, indicating the model's capacity to detect 72% of positive instances within the dataset accurately. In the interim, the macro-recall score, determined by calculating the mean recall value across all categories, is 60%. The observed score suggests that the model's performance may exhibit variability when applied to different classes, indicating the presence of potential obstacles specific to each class. The evaluation of precision, a crucial criterion in the field of classification, is also conducted. The microaccuracy score of the model is 72%, signifying that a significant proportion of the 72% of positive predictions provided by the model are accurately classified.



Figure 2: Scatter Plot

Nonetheless, the macro accuracy score, which denotes the mean precision value across all classes, exhibits a slightly diminished value of 57%. The observed mismatch underscores the fact that the precision levels of the model exhibit variation among distinct classes, indicating the need to focus on the performance of individual classes.

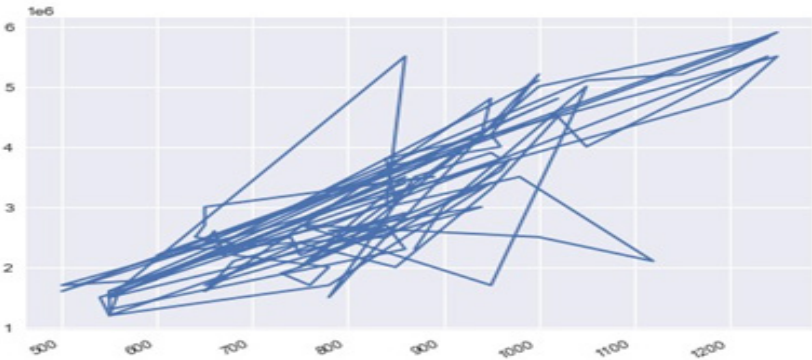


Figure 3:Line Plot

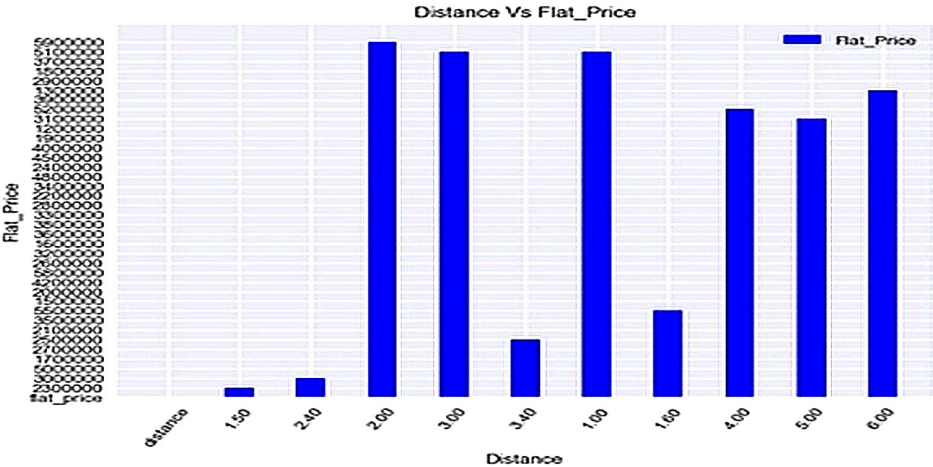


Figure 4:Bar Plot (Distance & Flat_price)

Surprisingly, an R-squared (R2) score is presented, commonly used in regression models rather than classifiers. The R2 score, with a remarkable value of 99%, indicates a high degree of data alignment, albeit its utilization in a classification context is atypical. Similarly, using mean square error (MSE) and mean absolute error (MAE) is demonstrated, commonly employed metrics specifically designated for regression-oriented endeavours. The mean squared error (MSE) exhibits a relatively small value of 0.1325, indicating minimal error.

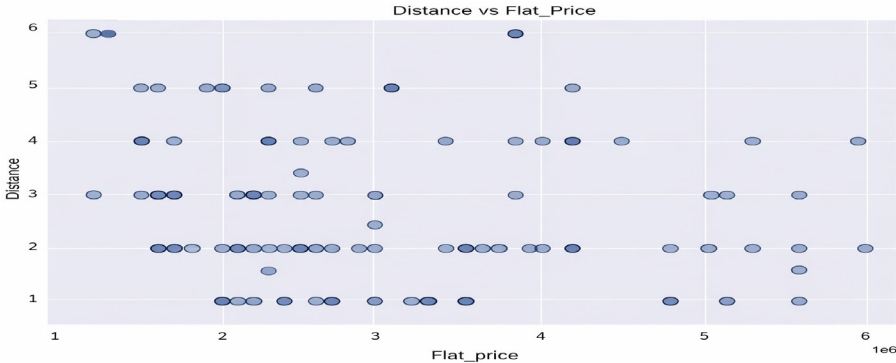


Figure 5:Line Scatter

However, its significance in the context of classification tasks remains uncertain. The mean absolute error (MAE), which has a value of 0.525, is a metric that measures the average absolute difference between predicted and actual values .

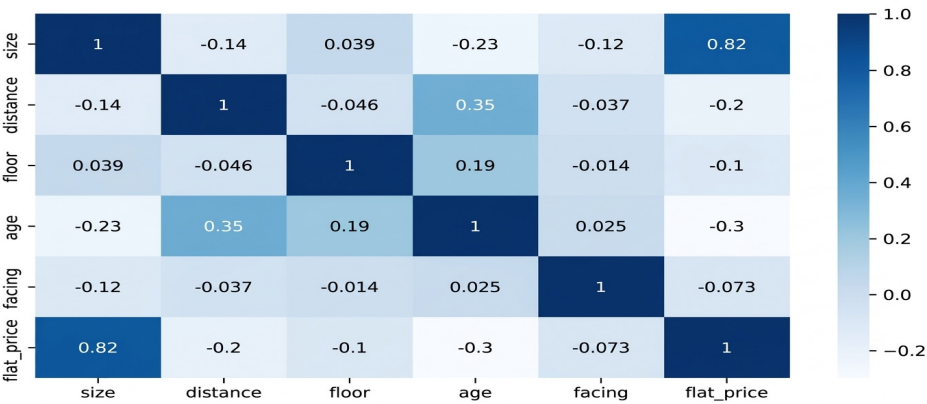


Figure 6:Heat Map

All the prediction shows in Table 2. However, its suitability for classification tasks is still uncertain. Finally, including the log loss measure is noteworthy as it is a widely accepted standard for assessing the performance of probabilistic classifiers. The model’s probability forecasts may lack appropriate calibration since a value of 0.98 suggests suboptimal performance in calibration.

Size , Flat_price, Floor

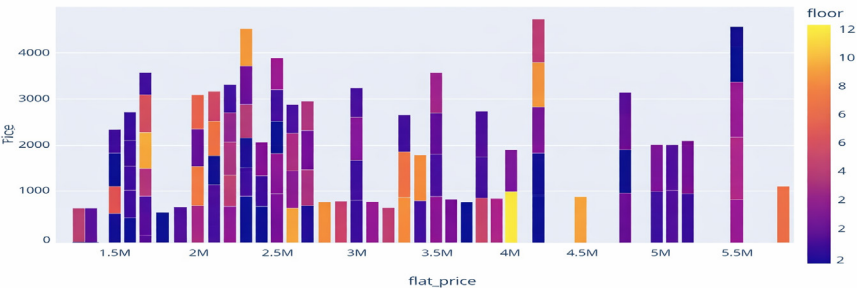


Figure 7:Bar Plot Size, Flat & Floor

Typically, lower values are preferred for models that exhibit superior calibration. The investigation commences by transitioning to the visualizations, namely a line plot that illustrates the correlation between size and flat price.



Figure 8:Bar Plot Size ,Flat_price & Facing

The plot elucidates the relationship between flat prices and flat size, offering prospective insights into the dynamics of size-price interactions. Subsequently, a heat map is presented, a commonly used method in data visualization to depict the relationship between different elements in a dataset. Heat maps are a valuable tool for data analysis as they facilitate the identification of patterns and correlations between variables.

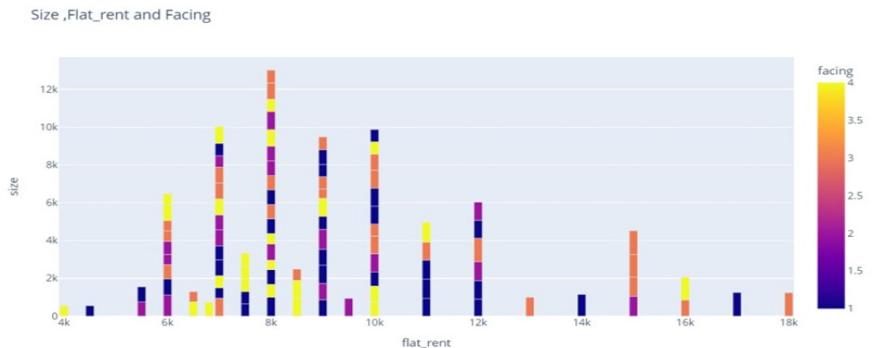


Figure 9:Bar Plot Size,Flat_rent & Facing

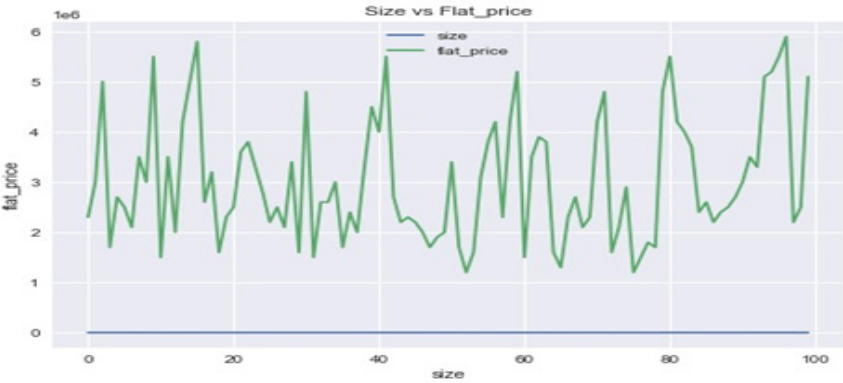


Figure 10: Log loss

They play a crucial role in the data exploration and feature selection processes. Heatmap of the propose methods are shown in Figure 6. The bar plot (size, flat price, and floor) is a visual tool to discern patterns and tendencies within flat pricing, sizes, and floor levels(). The figure facilitates the identification of correlations between flat size, floor level, and price by examining how price fluctuations vary across different floor levels for various flat sizes. The proposed methods' bar plot is shown in Figure 7: Bar Plot Size, Flat_Price & Floor. The bar plot examines the relationship between flat pricing, sizes, and facing orientations. Its visualization provides insights into the variations in flat prices based on different facing directions for apartments of various sizes. Figure 8: Bar Plot Size, Flat_price & Facing shows the proposed methods' bar plot. Finally, the bar plot examines the relationship between the size of flats, rental pricing, and floor levels, providing valuable insights into their interplay. The proposed methods' bar plot is shown in Figure 9: Bar Plot Size, Flat_rent & Facing. The tool allows for analyzing rent price patterns with various variables, improving decision-making. The evaluation outcomes and visual representations fully depict the model's performance and the interconnections within the data. The selection of appropriate assessment metrics and visualizations is crucial, as they should correspond with the specific task and model type. While regression tasks may benefit from using specific metrics and plots, choosing those most suitable for the work

at hand is important. These observations can guide future refinement of the model and analysis of the data, facilitating a more comprehensive comprehension of the dataset and improving the model's performance in areas that require attention. Logloss of the proposed methods are shown in Figure 10: Logloss. The scatter of the proposed methods are shown in Figure 5:Line Scatter.

Conclusion

This study aims to assess the efficacy of a long-short-term memory (LSTM) classifier in managing a particular dataset. The model demonstrates a significant level of accuracy, reaching a notable rate of 72%. This outcome provides empirical evidence that the model possesses practical skills for categorization. The F1 score, a crucial metric used to evaluate precision and recall, reveals that the micro F1 score is 72%, while the macro F1 score exhibits a somewhat lower value of 57%. This implies that the model demonstrates satisfactory performance in general, but it may face difficulties, particularly with minority classes, as evidenced by the comparatively lower macro F1 score. Both micro- and macro-level recall scores highlight the model's efficacy since positive values indicate its capacity to recognize instances accurately. The observed heterogeneity in recall scores highlights the presence of distinct obstacles linked to various classes, which can be attributed to the diversity of the dataset. The precision score of 72% suggests that a significant number of optimistic predictions exhibit accuracy.

Nevertheless, the marginal decrease in the precision score at the macro level underscores the necessity of enhancing performance in particular categories that may necessitate prioritization. The R2 score, commonly employed in regression analysis, demonstrates a robust correlation between variables, as indicated by its substantial value of 99%. This observation suggests the alignment of data, which is a significant aspect of the assessment of models. Although mean square error (MSE) and mean absolute error (MAE) have been commonly used as statistical measures, their appropriateness for classification tasks is still questionable. The log loss metric is used to evaluate the performance of a model and is considered a

significant tool for assessing the effectiveness of probabilistic classifiers. A range of visual representations, such as line plots, heat maps, and bar graphs, play a significant role in revealing patterns and trends about flat prices, sizes, and floor levels. The selection of these visualizations is carefully made to offer a thorough understanding of the dataset and to pinpoint specific areas where improvements can be made to enhance the model's performance. The careful selection of suitable assessment measures and visualizations is of utmost importance to acquire a comprehensive understanding of the dataset and improve the model's performance in areas that necessitate enhancement. The objective is to thoroughly comprehend the dataset to improve the model's efficacy within those domains.

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