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Office Building Rental Prediction Model Based on Locational Determinants

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Abstract: The importance of locational determinants in determining rental rates in the office market has long been acknowledged and unquestionably become the significant factor for assessing the rental potential of various property types. Nevertheless, the rapid progressing research that discovers the effect of locational determinants on the rental, limited study that was deeply looked into the provision of location to the rental mainly in Malaysia cases. Thus, this study aims to develop a predictive model for office building rentals based on a comprehensive analysis of locational determinants. To achieve the aims of this study, the objectives was outline which are to identify the determinant factors of location and to analyse the significant determinant factors. Through the application of machine learning, this study captured the intricate connections between rentals and different location-related factors. By leveraging advanced algorithms which are decision trees, random forests, support vector machines and gradient boosted trees, the model can effectively handle diverse datasets, encompassing variables such as proximity to central business districts, access to public transport network, neighbourhood and amenities, and traffic condition. Through rigorous data collection and pre-processing, this study constructs a robust dataset comprising historical rental dataset collected in the city area of Kuala Lumpur, Malaysia acquired from Property Services Department (JPPH) were used to train and validate the predictive model via R-squared performance metrics. The results indicate that proximity to Central Business District (CBD) emerges as a significant determinant with the most contribution to the model's prediction, with offices located in close proximity commanding higher rentals. This study provides valuable insights into the prediction of office building rentals based on locational determinants, offering a practical tool for stakeholders in the real estate industry.

Keywords: Office rentals, determinants, machine learning techniques, predictive model

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1. Introduction

The office rental market is a vital component of the commercial real estate sector, serving as a catalyst for economic growth, business operations, and urban development. It is a dynamic and multifaceted market influenced by various determinants that shape the demand, supply, and pricing of office spaces (Kołodziejczyk et al., 2020). Understanding these factors is crucial for investors, developers, and tenants seeking to navigate this ever-evolving landscape and make informed decisions regarding office rentals (Shokoohyar et al., 2020). Building upon previous research, numerous studies have explored the determinants of office rentals, providing valuable insights into the relationship between these determinants and rental dynamics. For instance, the economic determinants (Coffey et al., 2022; Lorenz et al., 2022), building certifications (Plebankiewicz et al., 2019; Wadu Mesthrige & Chan, 2019), building's physical structures (Bera, 2019; Jalali et al., 2019) and locational (Nurzukhrufa et al., 2018; Wan Rodi et al., 2019). Considering the extensive scholarly discourse, it is irrefutable that locational determinants have emerged as the most important standard for assessing the intrinsic value and rental potential of diverse property types (Bera, 2019). The centrality of these determinants extends beyond theoretical postulations, permeating the practical domain of valuation sectors within the Malaysian market (Adnan et al., 2012). As such, it was crucial to provide a comprehensive overview on the locational determinants, shedding light on their significance and interplay within the broader context of office building.

However, increase in complexity and competitiveness of the office building market necessitate the development of advanced tools and models to guide stakeholders in their decision-making processes. Traditional approaches to office building rental valuation often fail to capture the intricate nuances associated with location-based determinants (Ezra et al., 2018). In recent years, a certain computing technique named the machine learning has emerged as a powerful methodologies and techniques that enables the extraction of valuable insight from vast and complex real estate datasets. By leveraging the advanced algorithms and computational capabilities, machine learning has the potential to enhance various aspects of the real estate sector, including property valuation, rental predictions, market analysis, and investment strategies (Pai & Wang, 2020; Pinter et al., 2020). Real estate datasets are often vast and complex, comprising diverse variables and factors that influence property values and rental prices. Traditional statistical approaches may struggle to effectively process and analyse such datasets, leading to limited insights and potentially overlooking important trends (Cheung et al., 2021).

By leveraging the power of machine learning, this study seeks to bridge this gap by designing a prediction model that incorporates a wide array of locational determinants to accurately predict office building rentals and determine the significant of the determinants. The rationale behind this study lies in the potential for such a model to revolutionize the commercial real estate industry, empowering investors, developers, and tenants with robust insights into the relationship between location and rental valuations.

2. An Overview of Office Rentals

Office rentals are an essential component of the commercial real estate market given that they generate income for investors and property owners while giving companies a dedicated space to conduct their operations (Ma et al., 2018; Nurzukhrufa et al., 2018). Office rental is the process of renting office space to organisations or people for a predetermined amount of time. It involves the legal arrangement for the use of a specific space inside a business building or office complex between a landlord or property owner (lessor) and a tenant (lessee) (Shokoohyar et al., 2020). Office rentals have a significant impact on businesses, influencing their financial performance, operational efficiency, and overall productivity. For tenants, office rentals represent a significant cost and strategic decision, as it affects their budgeting, location choice, and long-term growth plans (Nurzukhrufa et al., 2018). Property owners and investors rely on office rentals as a source of income and as an investment opportunity, with rental rates and occupancy levels directly influencing the financial performance and value of their properties. Understanding the dynamics of office rentals involves analysing factors such as rental trends, market conditions, tenant preferences, lease negotiations, and the broader economic context. Researchers, policymakers, real estate professionals, and businesses conduct studies and analyses to gain insights into office rental markets, informing decision-making, investment strategies, and policy formulation related to commercial real estate (Czerniak & Rubaszek, 2018; Hekman, 1985; Nurzukhrufa et al., 2018).

2.1 Locational Determinants

The symbiotic relationship between locational determinants and office rentals unveils a complex tapestry of influences that shape the pricing dynamics within the real estate market (Ojok, 2018; Safian & Nawawi, 2013). It was well-established for any real estate market that prices, and rentals were varied over locations (Bera, 2019). This study endeavours to unravel the enigmatic connection between these factors and rentals, transcending the mundane and delving into the nuanced domain of locational desirability, ascertaining the intricate multitude of variables that underpin the rental rate prediction for office buildings with machine learning as approach. Here, four (4) variables were provided by acquiring previous literature pertaining the locational determinants.

In essence, the undeniable magnetism of office buildings within or near Central Business District represents a harmonious amalgamation of location, accessibility, amenities, and serendipitous synergies (Hui et al., 2015). The concentration of businesses in the CBD leads to increased opportunities for networking, collaboration, and knowledge spill overs. This clustering effect can create a positive feedback loop, driving up the demand for office spaces and, consequently, rental prices in the vicinity (Nurzukhrufa et al., 2018). The dynamics of the market and supply constraints may also have an impact on the correlation between rental prices and the distance to the CBD. Due to strong rivalry and a lack of rental options, rental prices frequently increase in highly sought-after CBD areas with little available space (Ojok, 2018). The availability of properties typically rises as one travel farther from the CBD, providing a wider range of options and possibly lower rental rates (Kampamba & Cloete, 2015).The multifaceted exploration of CBD factors in previous research has unfurled an opulent tapestry of urban grandeur, punctuated by the resounding crescendo of commercial allure. For instance, revelation from Bera (2019) signifies that distance to CBD significantly impact the office rentals by 3.45 cent when distance increases.

The interaction between accessibility and the infrastructure of transportation emerges as a key factor in the world of urban development and the dynamics of office rentals. Strong transport networks provide efficient mobility and seamless connectivity, which act as essential catalysts and have a significant impact on office rentals (Nurzukhrufa et al., 2018). Strategic placement of office buildings within accessible locales, coupled with the presence of efficient transportation modes, bestows upon these spaces an undeniable advantage (Udoekanem et al., 2015). The proximity to major transportation hubs, arterial roads, and public transit networks enhances the ease of commuting for employees and clients alike, creating an aura of convenience and attractiveness that reverberates in the rental valuation's domain.

Demand on rental rates for office building can be significantly impacted by the ebb and flow of traffic congestion on the roads (Aliyu et al., 2015). Congested roadways, riddled with traffic jams and prolonged commuting times, pose significant challenges for employees and clients in reaching their desired office locations. Businesses situated in areas plagued by chronic traffic congestion may face dwindling interest and reduced rental demand, as the arduous commute dampens the allure of these spaces (Kopczewska & Lewandowska, 2018). Conversely, office spaces strategically located in areas with smooth traffic flow benefit from enhanced accessibility, bolstering their rental attractiveness.

Prospective tenants and businesses meticulously assess the surrounding environment before committing to office spaces, considering factors such as neighbourhood and amenities (Aliyu et al., 2015; Wan Rodi et al., 2019). Office space access to necessary amenities and services has a big impact on rental decisions (Bera, 2019). The convenience of having banking establishments, post offices, medical facilities, and other necessary services available close to where their offices are located is valued by businesses, employees, and clients (Ojok, 2018). A sense of comfort and efficiency is fostered by neighbourhoods with a wide variety of services, which raises the appeal of office space there and may result in higher rental (Yusuf et al., 2021).

2.2 The Role of Machine Learning for Rental Prediction Model

It is crucial to investigate cutting-edge approaches that improve the precision and prognostication of rental prediction models. The application of machine learning techniques has revolutionised real estate research in recent years, giving researchers access to cutting-edge tools and methodologies. Machine learning techniques provide powerful tools for analysing complex datasets and uncovering patterns that drive rental prices.

Feature selection and extraction are essential steps in creating reliable rental prediction models, and machine learning algorithms provide researchers with sophisticated techniques for these tasks (Kendale et al., 2018). unnecessary or irrelevant data, speed up the modelling process, and concentrate on the important factors that affect rental prices by automatically identifying the most significant variables and extracting pertinent features from the dataset (Ahmad et al., 2018). This increases the results' interpretability and the predictive accuracy of the model, enable the user to pinpoint the key factors influencing rental dynamics. By leveraging historical rental data and incorporating locational determinants, predictive models can be trained to identify relationships, correlations, and non-linear dependencies between variables (Irjet et al., 2017). Supervised learning algorithms, such as regression models, decision trees, or neural networks, can be employed to develop predictive models that capture the intricate relationships between locational factors and office building rentals (Phan & The Dahn, 2018). Corroborating the findings from previous literature, these algorithms were effective at predicting property selling price (Baldominos et al., 2018), estimating rentals (Zhou et al., 2019) and forecasting agricultural land values (Er, 2018). The utilization of machine learning techniques allows for the development of robust models capable of handling diverse datasets and adapting to changing market conditions (Rutzen et al., 2017).

Machine learning's capacity to adapt and learn from new data in real-time is one of its notable advantages in rental prediction models (Hutter et al., 2019; Kaytan & Aydilek, 2017). This adaptability enables the capture of shifting market dynamics, developing trends, and new variables influencing rental rates (Dimopoulos & Bakas, 2019; Niu & Niu, 2019). Predictions can be improved, and results can be made into actions in a dynamic real estate market by regularly updating the model with new data. This in-the-moment analysis equips researchers to decide wisely and offer insightful information to industry stakeholders (Cheung et al., 2021). Due to the high scalability of machine learning techniques, analysts can use their rental prediction models in a variety of geographic locations, property types, and market niches (Niu, 2019; Rutzen et al., 2017). For researchers looking to broaden their analyses beyond a particular market or property type, this transferability is priceless. By creating scalable models that can be applied to a variety of datasets by utilising machine learning algorithms, enabling thorough comparative analyses and insights across various real estate markets.

To advance the field and conduct ground-breaking research, it is crucial to embrace the transformative role that machine learning plays in rental prediction models. When machine learning techniques are integrated, processes become more effective, prediction models are optimised, hidden insights are revealed, markets can adapt to changing conditions, and findings are scaled and transferable. Machine learning can greatly enhance the precision, effectiveness, and practical applicability of rental prediction models by utilising machine learning, significantly expanding the field of real estate research and providing industry stakeholders with priceless information for well-informed decision-making.

3. Methodology

3.1 Data Collection

The Kuala Lumpur city centre has been meticulously chosen as the focal study area. Considering the statistics data from Department of Statistics Malaysia (DoSM), it was recorded that this area recorded the highest rental transactions compared to other regions. The data for this study has been meticulously compiled using an observation checklist through the consideration of the locational determinants as expounded in the literature. These determinants encompass an intricate interplay of factors, including the proximity to the central business district, access to public transport network, traffic condition, and neighbourhood and amenities. The inherent volatility of rentals within the vibrant of Kuala Lumpur city centre area were subjected to rigorous test using these determinants as the analytics components named the attributes. Notably, the primary datasets have been meticulously procured from the Valuation and Property Services Department (JPPH), encompassing of 722 office rental transactions from year 2018 to 2023, subjected from listed office building by the JPPH at Kuala Lumpur, Malaysia. Table 1 depicts on the list of the attributes.

Table 1 - List of attributes and descriptions

Office rental determinants	Description
Proximity to Central Business District	Distance of building to CBD
Access to public transport network	Public transport access
Traffic condition	Traffic condition
Neighbourhood and amenities	Available amenities at the surrounding area

3.2 Predictive Analytics

Predictive analytics is widely recognized as an indispensable foundation that drives digital transformation initiatives spanning diverse sectors and global business processes (Attaran et al., 2018). Within the real estate domain, the efficacy of predictive analytics assumes paramount importance in accurately discerning and forecasting market trends (Fraihat et al., 2021). The inseparable connection between predictive analytics and machine learning arises from the prevalent adoption of machine learning algorithms in constructing predictive models. These models possess the ability to adapt to new data or values over time, thereby generating the requisite outputs (Kendale et al., 2018). In relation to this study, the predictive analytics via Rapid miner studios were executed by predicting office rental based on the locational determinants. Algorithms in machine learning were used to develop these models and once the statistical analysis were carried out, it identifies trends and patterns in data.

3.3 Machine Learning Modelling Framework

Figure 2 presents the flowchart of the machine learning models of this study. Initial data were collected from the Valuation and Property Service Department (JPPH). The data consist of the property valuation records for office building located at the district of Kuala Lumpur from year 2018 to 2023. In this study, different machine learning models were tested on the office building dataset based on different features selection groups. Four (4) machine learning algorithms were used namely Decision Tree Regressor, Random Forest Regressor, Gradient Boosted Trees and Support Vector Machine algorithms. Additionally, each model in each feature selection group was also evaluated according to different training and validation splitting approaches namely basic split.

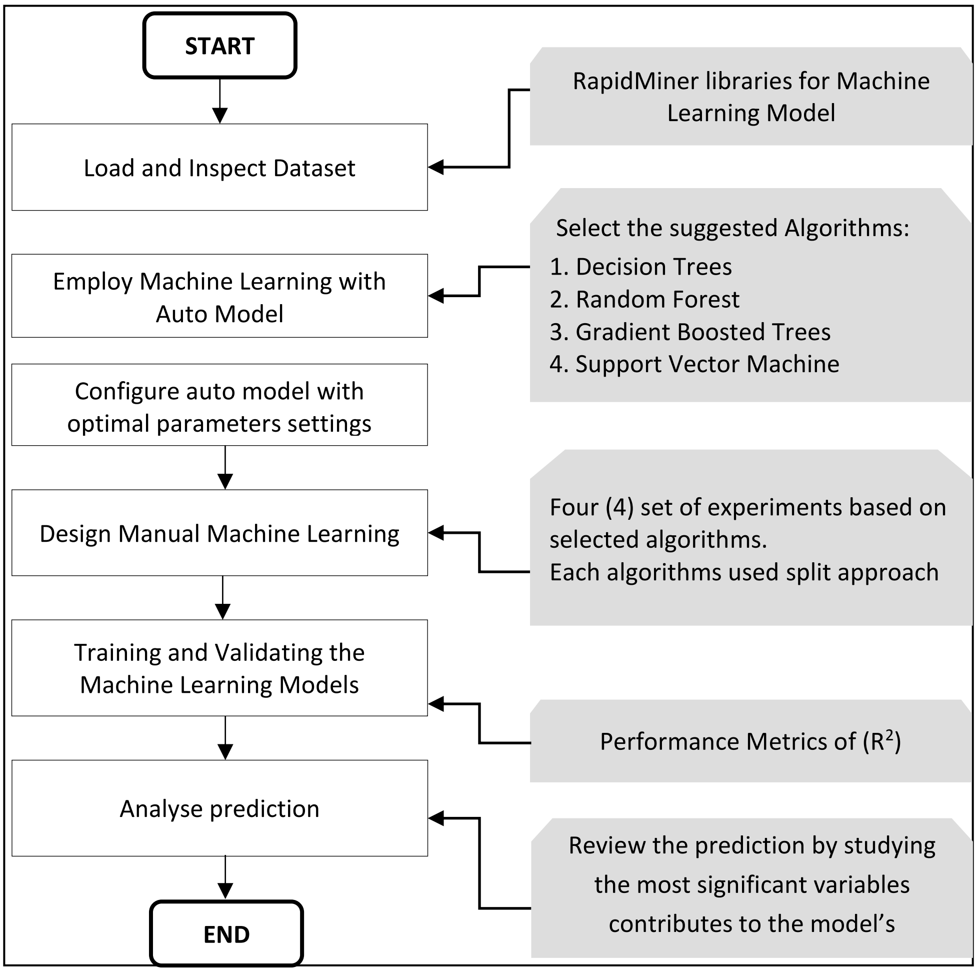

Fig. 1 - Machine learning modelling framework
Source: (Researcher, 2023)

3.4 Auto Model

The prediction model for office rentals in this study benefitted from the implementation of an automated model selection process. This sophisticated procedure recommended a set of algorithms to be employed in the prediction model. The number of algorithms suggested by the auto model corresponds to the number of experiments conducted throughout the study. Detailed information regarding the algorithm recommendations generated by the auto model is succinctly presented in Table 2, thereby providing a comprehensive overview of the selected algorithms that were rigorously assessed and evaluated in the pursuit of accurate office rental predictions.

Table 2 - Selection of algorithms by auto model

Experiments	Algorithms selection
1	Decision Tree
2	Random Forest
3	Support Vector Machine
4	Gradient Boosted Trees

3.5 Optimal Parameter Settings

The utilisation of optimal parameter settings serves the primary objective of minimizing prediction errors and enhancing prediction accuracy. This concept has been commonly employed in prior research pertaining to prediction analysis, as exemplified by Zhang (2021) application of hyperparameter tuning for algorithm configurations using Python. The optimal parameter strategy acts to optimise the machine learning algorithms, enabling it to function as a proficient prediction model through parameter modifications. An optimization search is employed to determine the most suitable Machine Learning settings, which are intricately dependent on the underlying dataset structure. Table 3 depicts the optimal parameters settings for the selected algorithms.

Table 3 - Optimal parameters settings

	List of algorithms	Maximal depth	Number of trees	RBF	C	Error rate
1.	Decision Tree	10	NA	NA	NA	20.5%
2.	Random Forest	7	100	NA	NA	25.2%
3.	Support Vector Machine	NA	30	0.005	100	22.5%
4.	Gradient Boosted Trees	7	30	NA	NA	23.6%

Source: (Researcher, 2023)

3.6 Training Approach

The split training approach is a fundamental technique employed in machine learning and predictive modelling to evaluate model performance and enhance generalization capabilities. By dividing the dataset into training and testing subsets, this approach will train models on a representative portion of the data and assess their ability to generalize to unseen instances. Figure 2 portrayed the general interface of split training approach.

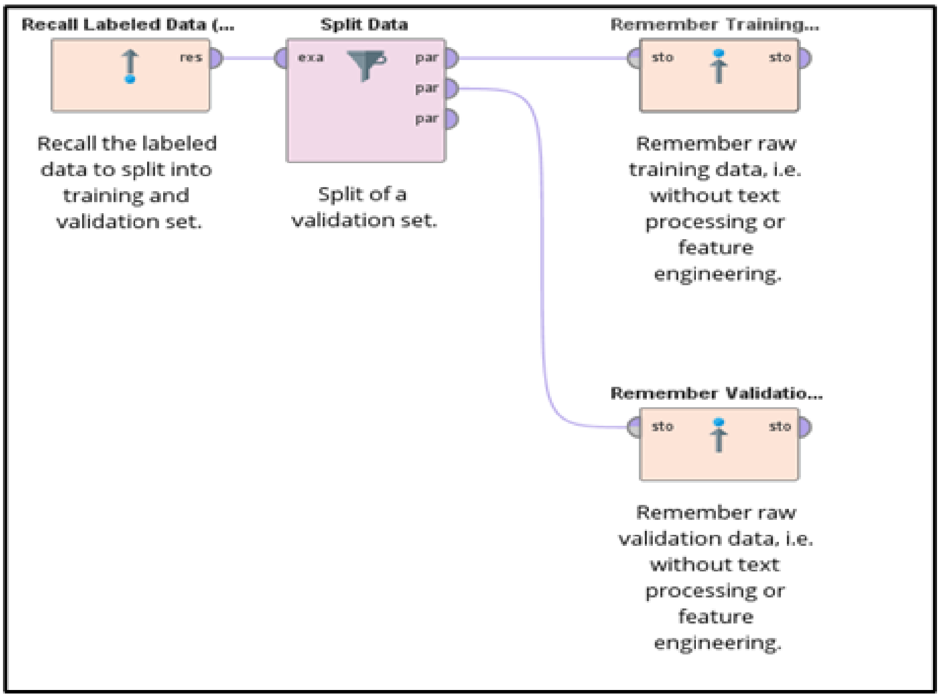

Fig. 2 - Split training interface
Source: (Researcher, 2023)

3.7 Performance Metrics

During the development of the office rental prediction model, this study employed a performance measurement known as the coefficient of determination, commonly referred to as "R-squared". R-squared is a statistical metric used to quantify the extent to which the variations in the dependent variable can be explained by the independent variables (Čeh et al., 2018). A higher value of R-squared indicates a better fit of the model under examination. Mathematically, R-squared can be calculated using Equation 1, which elucidates the relationship between the

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - y)^2} \quad (1)$$

Source: (Akoglu et al., 2018)
Equation 1 *Equation of R-squared*

4. Results and Discussion

This section presents the findings derived from the application of machine learning models for the purpose of predicting office rentals. The results were obtained through a meticulous two-fold process, comprising implementation and observation. In the initial step, the efficacy of each machine learning algorithm was rigorously assessed by evaluating its prediction accuracy. Subsequently, in the second step, a comprehensive analysis was conducted to determine the weightage of each determinant, representing the independent variables, in their contribution to the prediction of rentals.

4.1 Machine Learning Prediction Results Based on Split Approach

The prediction outcomes were derived by utilizing locational determinants to investigate the impact of variables on office rentals. These determinants were examined employing the recommended algorithms suggested by the auto model. The outcomes are delineated in Tables 3.

Table 3 - Predictions of rentals based on selected algorithms

	Prediction			
Observed value	**Decision Tree**	**Random Forest**	**Support Vector Machine**	**Gradient Boosted Trees**
RM118.75	RM110.55	RM114.75	RM98.70	RM180.10
RM172.24	RM155	RM266.89	RM111.39	RM89.67
RM251.66	RM251.90	RM266.95	RM255.85	RM267
RM276.60	RM289.72	RM290.92	RM301.10	RM295.94
RM429.18	RM411.67	RM423.90	RM423.78	RM544.83
RM637.29	RM567.21	RM621.89	RM877.56	RM622.54
RM706.40	RM850.90	RM788.23	RM655.90	RM711.67

Source: (Researcher, 2023)

The findings illustrate that various algorithm with distinct results, as demonstrated. By incorporating four (4) distinct algorithms and employing locational determinants, this study enables predictions of office rentals. Based on these predictions, the study determines the most influential variables among the locational determinants, as indicated by the correlation coefficient R-squared. The highest R-squared value signifies the significance of the variables based on the observed "R^2." Figure 3 indicates the R-squared value of every variable included in this study.

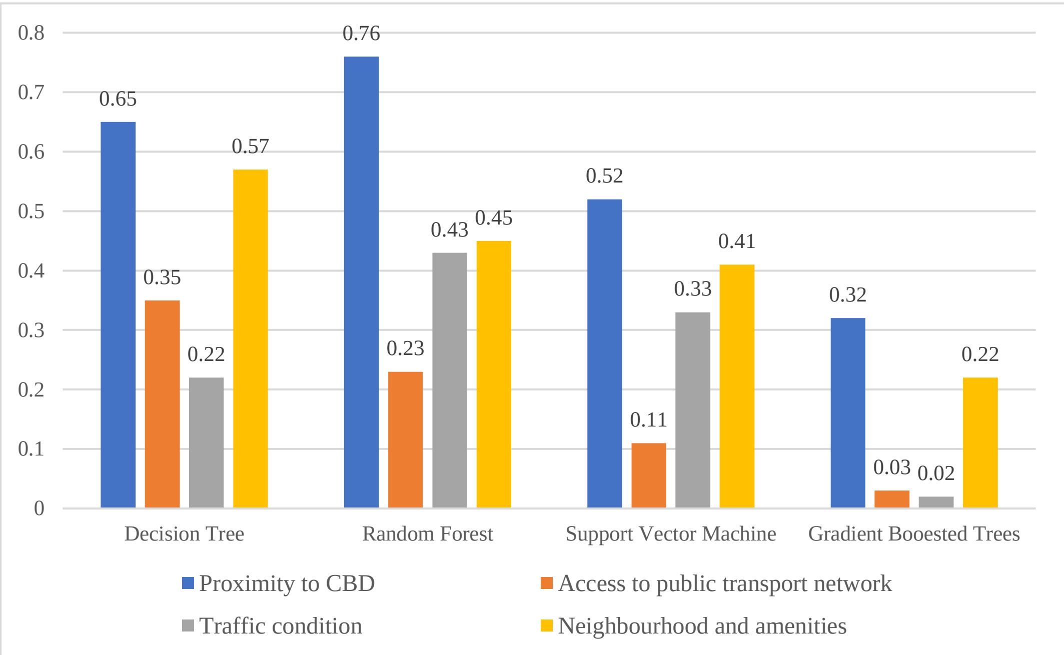

Fig. 3 - Variables contributions
Source: (Researcher, 2023)

With the outcomes derived from the application of four distinct types of algorithms, Figure 3 portrays the variable contributions within the locational determinants to predict office rentals. Significance of variables was assessed based on the R-squared scores. Notably, proximity to central business districts emerges as the most influential variable, exhibiting the highest score when compared to other variables. This finding aligns with established literature, emphasizing the intensified networking, collaboration, and knowledge spill over opportunities that arise from the concentration of businesses within the CBD (Nurzukhrufa et al., 2018). The consequential clustering effect establishes a reinforcing cycle, propelling the demand for office spaces and, consequently, driving up rental prices in the surrounding area. Conversely, the escalating competition and scarcity of available rental options in highly coveted CBD zones contribute to the frequent escalation of rental prices (Ojok, 2018).

Meanwhile, neighbourhood and amenities also show a good contribution towards the predictions of rentals. It demonstrates a commendable contribution, scoring a moderate R-squared value of 0.57 for decision trees. Consistent with existing literature, the availability of necessary amenities and services holds substantial sway over office rental decisions (Bera, 2019). Furthermore, the appeal and potential for higher rental prices within neighbourhoods with a diverse range of services can be attributed to the cultivation of comfort and operational efficiency within office spaces (Yusuf et al., 2021).

Despite the influence of access to public transport networks and traffic conditions on office building rentals, the analysis revealed that these factors did not contribute significantly to the prediction model. The low R-squared scores obtained from running the data through four (4) different algorithms indicate that these variables lack significance in explaining the rental predictions. While access to public transport and traffic conditions are often considered important factors in real estate studies (Aliyu et al., 2015; Nurzukhrufa et al., 2018), their limited impact on office building rentals in this study suggests that other determinants play a more dominant role. It is possible that other locational factors, such as proximity to central business districts, neighbourhood characteristics, or amenities, exert a stronger influence on rental prices.

The findings underscore the importance of thoroughly analysing and understanding the specific context and dynamics of the office real estate market. While access to public transport networks and traffic conditions did not show significant predictive power in this study, the investigation of other locational factors remains crucial for understanding and accurately predicting office building rentals.

5. Conclusion

In conclusion, this study has focused on the development of an office building rental prediction model based on locational determinants. Through an in-depth exploration of office rentals determinants, including proximity to the CBD, accessibility and transportation infrastructure, neighbourhood and traffic condition, this study has shed light on the complex dynamics and interplay between these determinants. The findings of this study highlight the significance of locational determinants in predicting office rentals. Proximity to the CBD emerged as a key factor, with its positive impact on rental prices attributed to enhanced accessibility, networking opportunities, and the prestigious image associated with being in or near the economic and commercial hub of a city.

Overall, this study provides valuable insights into the factors that drive office rental prices, enabling stakeholders in the real estate industry to make informed decisions and predictions. The developed prediction model, incorporating machine learning techniques and leveraging locational determinants, can serve as a powerful tool for accurately estimating rental prices and assisting in strategic planning for investors, property developers, and real estate professionals. However, it is important to acknowledge the limitations of this research. The model's accuracy and effectiveness depend on the availability and quality of data used for training and validation. Additionally, factors beyond locational determinants, such as market conditions and economic factors, may also influence rental prices and should be considered in future research.

This study provides a foundation for further exploration and refinement of office rental prediction models based on locational determinants. As the real estate industry continues to evolve, leveraging machine learning and predictive analytics in rental predictions can facilitate more informed decision-making and contribute to the efficient and sustainable development of office spaces.

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