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Machine learning prediction of quality of life: Insight from property crime and tropical climate analysis

Anis Zulaikha Mohd Zukri[1], Siti Rasidah Md Sakip[1,2], Suraya Masrom[3]
[1]Department of Built Environment and Technology, Universiti Teknologi MARA, Seri Iskandar Campus, Perak, Malaysia
[2]Green Safe Cities Research Group, Department of Built Environment Studies and Technology, College of Built Environment, Universiti Teknologi MARA, Perak, Malaysia
[3]Computing Sciences Studies, College of Computing, Informatics and Media, Universiti Teknologi MARA, Perak, Malaysia

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ABSTRACT

The study addresses the prediction of quality of life, leveraging machine learning models with a focus on health, socioeconomics, subjective well-being, and environmental indicators. Thus, this study aims to evaluate the efficacy of machine learning in quality-of-life prediction based on property crime and temperature. Five machine learning algorithms were used to be empirically compared namely generalized linear model (GLM), random forest (RF), decision tree (DT), gradient boosted tree (GBT) and support vector machine (SVM) are compared empirically. The performance of each machine learning algorithm in predicting the quality of life has been observed based on the attributes of property crime and tropical climate (temperature). Despite initial low correlation with quality of life, temperature significantly contributes to specific algorithms, enhancing predictive accuracy. This shows the complexity of machine learning impacts. SVM emerges as the best-performing algorithm, followed by RF and DT. The findings highlight the importance of seemingly unrelated factors in prediction outcomes. This paper presents a fundamental research framework useful for helping educators and researchers to explore in depth quality of life prediction with using property crime and temperature as a factor.

Corresponding Author:

Siti Rasidah Md Sakip
Department of Built Environment and Technology, Universiti Teknologi MARA
Perak Branch, Seri Iskandar Campus, Malaysia
Email: sitir704@uitm.edu.my

1. INTRODUCTION

The concept of predicting quality of life has been extensively explored in various studies and papers, utilizing different methods and indicators. Common strategies involve evaluating health status [1]–[3], socioeconomic elements [2], subjective well-being [4], [5], and environmental conditions [6], [7] to forecast and assess quality of life. However, in the realm of urban geography and urban studies, there has been limited attention given to the connection between crime and quality of life, as noted by [8]. Notably, investigations into the intersection of quality of life and crime have been conducted by several researchers including [8]–[15].

Furthermore, numerous studies, including Ranson [16] affirm a correlation between weather and crime. Weather's pivotal role in crime prediction is underlined, with hypotheses proposing that weather can impact social interaction-related crime rates. Anderson [17] connect weather with crime production and Becker's model, while external factors like heat can influence aggression. Research by Ranson [16] reinforce the link between temperature and aggression. Cohn [18] acknowledges weather's role in crime theories and it is behavioral effects. The influence of weather on behavior has garnered attention [18], [19], highlighting its relevance in crime dynamics.

The weather-crime relationship received limited attention prior to the 1960s. Several researchers highlighted later studies focusing on weather's impact on criminal behavior and psychology [18], [20]. Research suggests a direct link between weather and psychological triggers for violent crime [21], with traditional beliefs associating high humidity and temperature with aggression [22]. Temperature's influence on crime, especially violent crime, is a key focus [16], with higher temperatures correlating to increased crime rates [16]. Max temperature explains seasonal shifts in violent crime [18], [21], [23], tracing back to heightened aggression in summer [21]. Violent crime closely connects with temperature, unlike non-violent crime [21]. Max temperature and high humidity link strongly to violent crime, whereas min and average temperature have less impact [21].

Weather significantly influences human behavior, potentially affecting criminal actions stated by Jung *et al.* [23]. Weather conditions like temperature, rain, and wind impact outdoor activity and interactions, influencing opportunities for interpersonal crimes [22]. Heat hypothesis suggests high temperatures trigger aggressive behavior [17], [19]. Weather shapes crime patterns; "pleasant" weather keeps people indoors, reducing crime chances with capable guardians present. In contrast, inclement weather deters criminals due to discomfort and costs, affecting burglary attempts and stolen goods transportation [24]. "Pleasant" weather is linked to increased property crime [24].

This study expands on previous research by investigating the impact of property crime on quality of life in tropical climate regions. Unlike earlier investigations conducted by [8]–[15] which employed conventional statistical methods, the advancement of machine learning deem beneficial. Machine learning algorithms are constantly upgraded [25]–[27], promising great potential in wide domains of real life problems.

This study significantly builds upon existing quality-of-life research by introducing a novel approach involving the implementation of machine learning prediction. Through the utilization of three key constructs, this approach aims to enhance our current comprehension of the connections and associations between quality of life, crime, and weather. By incorporating machine learning techniques, this research seeks to provide a more sophisticated and comprehensive understanding of how these variables interact and influence one another. This approach holds the potential to uncover nuanced insights that traditional research methods might not capture, thus contributing to a deeper exploration of the intricate relationships between quality of life, crime patterns, and weather conditions.

2. RESEARCH METHOD

2.1. Data collection and datasets

Data of this study were collected using questionnaire survey that comprises of quality of life, domains. The section of questionnaire was developed based on the three constructs of the quality of life: physical, psychological, and social. To measure each construct of this study, a five-point Likert scale was employed, ranging from 1=strongly disagree to 5=strongly agree. Estimate for each construct was obtained using the average values of its indicators.

The questionnaire was administered to the residential area residents from a neighbourhood area at Taman Dato' Senu, Sentul Kuala Lumpur. The survey was carried out by face to face because this method solved some problems on the site, such as collecting data on the quality of life, allowing question in the questionnaire to be delivered in various ways until the respondents understand the requirements of the question and ensure that the instruction in the survey are followed. From the total of 317 questionnaire administered, 254 valid responses were used for the analysis, representing a response rate of 80%.

2.2. Correlations of variables

Table 1 lists the independent variables (IVs) in predicting the quality of life namely property crime and temperature. Based on pearson correlation test, the property crime presents a moderate relationship to the quality of life while temperature has very low correlation. Although with the weak association, it is interesting to observe how the temperature can contribute some influences on different machine learning algorithms.

The pearson correlation coefficient of 0.638 between property crime and quality of life indicates a moderate positive linear relationship between these two variables. As seen in Table 1, a value of 0.638 indicates a notable degree of association between property crime and quality of life, suggesting that areas or location with higher property crime rates tend to exhibit lower quality of life ratings, and areas with lower property crime rates tend to have higher quality of life ratings. The property crime index will encompass, such as theft, car/vehicle theft, motorcycle theft, lorry/van/bus theft, snatch theft, and burglary. The focus will be on understanding the relationship between temperature changes, the occurrence of criminal activity, and the level of satisfaction of residential people regarding their quality of life.

Table 1. Pearson correlation of each IV to the dependent variable (DV)

Attribute	Correlation coefficient
Property crime	0.638
Temperature	0.012

Consequently, two groups of features were selected for the machine learning model: i) quality of life with property crime and temperature, and ii) quality of life without temperature. These sets of features were included in Table 2 to facilitate the machine learning process by providing a clear differentiation of the variables utilized for analysis and prediction. Feature selection involves choosing a set of pertinent features or attributes to utilize in a machine learning model. The feature importance weights calculated for each feature in each algorithm, and the weights indicate the relative importance of each feature in the model. Analysing feature importance weights enables a deeper understanding of the factors driving the model's predictions. Features with higher importance weights are deemed to have a more substantial impact on the model's decision-making process, while those with lower weights may contribute less significantly or may even be considered irrelevant. This information is instrumental in comprehending how the model leverages various features to make accurate predictions, thereby aiding in model interpretation and validation.

Table 2. Features selection groups for the machine learning

Group	IVs	DV
Feature selection 1	Property crime, and temperature	Quality of life
Feature selection 2	Property crime	Quality of life

2.3. Machine learning

There were six machine learning algorithms has been suggested by RapidMiner AutoModel for the quality-of-life dataset. However, only five machine learning algorithms namely generalized linear model (GLM) [28], random forest (RF) [29], and decision tree (DT) [29], gradient boosted trees (GBT) [29], and support vector machine (SVM) [30] have been chosen for this study. Deep learning was excluded due to complexity of algorithm that causes long processing time to complete. Table 3 outlines the optimal hyper-parameters of each machine learning algorithm from the preliminary machine learning hyper-parameters tuning.

Table 3. Configuration of parameters

Algorithm	Optimal parameters	Error rate (%)
RF	Number of trees=60 Maximal depth=7	6.6
DT	Maximal depth=7	6.8
GBT	Number of Trees=30 Maximal depth=7 Learning rate=0.100	7.0
SVM	Kernal Gamma=0.050 C=1,000	5.8

The number of trees used in the preliminary hyper-parameters tuning of RF are 20, 60, 100, 140. For each of the four number of trees, three values of maximal depth (2, 4, 7) have been observed. The worst error rate was 7.3% with the number of trees equals 20, 60, 100, 140 and it is maximal depth was 2. The best error rate is 6.6% with the configuration given in Table 2.

For the DT, the range of maximal depth used in the preliminary testing is between 2 to 25. The highest error rate was 7.7% if the maximal depth is 2, which can be reduced to 7.0% with maximal depth 4. The error rate value remained consistent to 6.8% when the maximal depth was set to 7, 10, 15, or 25.

GBT has additional parameter namely learning rate besides number of trees and maximal depth. The minimum number of trees used in the preliminary algorithm tuning is 30 and the maximum is 150 with 2, 4, and 7 alternatives of maximal depth. The series of the learning rate was set between 0.001 to 0.1. The highest error rate achieved is 11.6% with 30 number of trees, 2 maximal depth and 0.001 learning rate. The lowest error (6.6%) can be observed when the number of trees remain 30 but the maximal depth and the learning rate were set to 4 and 0.1 respectively.

SVM uses Kernal Gamma and C (regularization) parameters, which were observed in the preliminary research between 0.005 to 5 for Kernal Gamma and 10-100 for C. The worse setting generated by SVM when the Kernal Gamma was 0.005 at 100 C, that reached to 74.9% of error rate. The best setting was 0.050 Kernal Gamma at 1,000 C to complete the prediction at 5.8% error rate only. For separating the training and testing datasets, the research split training approach with ratio of 60:40 percentages based on the configuration suggested by AutoModel RapidMiner. Therefore, from the 254 data, 62 of them were used for the machine learning training and 41 were used in the machine learning testing.

3. RESULTS AND DISCUSSION

This research presents two distinct sets of results. Firstly, Table 4 outlines the performance outcomes of machine learning in predicting the quality of life. This table can be used to compare each machine learning algorithm performance in accordance with the two-feature selection as shown in Table 2. Secondly, Figure 1 present in depth the presentation and discussion of how the machine learning algorithms are influenced by the two IV, property crime and temperature. The analysis of these results provides a comprehensive understanding of the interplay between machine learning, quality of life prediction, and the impact of property crime and temperature as IV.

Table 4. The performances result

Algorithm	RMSE (+/-std.dev)	R^(+/-std.dev)	Time to complete (s)
	Feature Selection 1		
GLM	0.345(+/-0.056)	0.612(+/-0.205)	9
RF	0.32 (+/-0.067)	0.626(+/- 0.261)	1
DT	0.327(+/-0.038)	0.654(+/-0.211)	5
GBT	0.367(+/-0.069)	0.568(+/-0.238)	84
SVM	0.339(+/-0.064)	0.666(+/-0.294)	76
	Feature Selection 2		
GLM	0.345(+/-0.056)	0.612(+/-0.205)	0.838
RF	0.32 (+/-0.039)	0.613(+/- 0.307)	0.243
DT	0.344(+/-0.038)	0.538(+/-0.332)	4
GBT	0.384(+/-0.067)	0.472(+/-0.365)	87
SVM	4.363(+/-0.025)	0.684(+/-0.094)	44

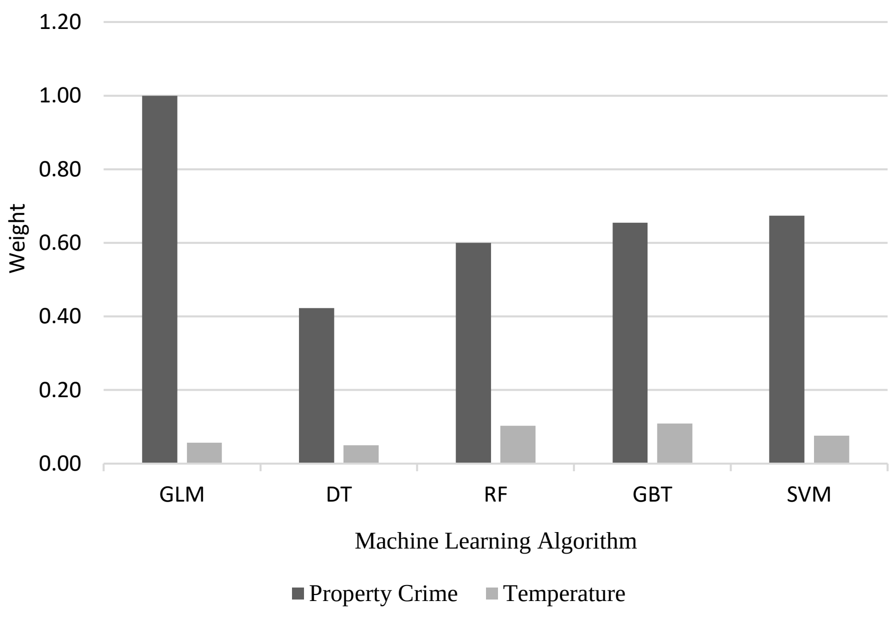

Figure 1. Weight of IVs in machine learning algorithm

Although temperature exhibits a low correlation according to the Pearson test when considered outside of machine learning algorithms, it is utility in enhancing predictive abilities becomes apparent within certain algorithms. Despite the initial low correlation value, Temperature manages to contribute valuable insights to specific algorithms, leading to improvements in their predictive accuracy. This shows how detailed and complicated its impact can be in the context of machine learning. Even factors that may seem unrelated can be important and improve prediction results. In terms of predictive accuracy, the root mean square error (RMSE) offers a measure of how close the model's predictions are to the actual values. Lower RMSE values indicate better predictive performance. Among the algorithms, the DT exhibited the lowest RMSE of 0.32 (+/-0.067), followed closely by RF with an RMSE of 0.327 (+/-0.038). These algorithms demonstrated more accurate predictions compared to the other models.

The coefficient of determination (R^2) measures how well the model's predictions match the actual data. A higher R^2 value indicates better alignment between predictions and actual values. In this case, SVM led with the highest R^2 of 0.666 (+/-0.294), indicating that it captured a substantial portion of the variance in the data.

Considering the combination of these metrics, particularly the RMSE, and R^2, SVM emerges as the best-performing algorithm in predicting quality of life. The higher R^2, and competitive RMSE indicates robust predictive capabilities and accurate results. However, practical considerations such as computational time should also be taken into account when selecting the most suitable algorithm for a specific use case. SVM took longer time than GLM, RF, and DT but shorter than GBT. Nevertheless, the time taken is considerable acceptable, which is less than a minute with feature selection 2.

Furthermore, it is interesting to gain insight into the contributions of each attribute that influences machine learning performance. Figure 1 presents the weights of the contributions calculated based on pearson correlation. These contributions collectively inform the predictive model with GLM, DT, RF, GBT, and SVM, providing a comprehensive understanding of each attribute's impact on the overall predictive accuracy across different algorithms.

The results in Figure 1 show five (5) different machine learning algorithms have varying levels of success in predicting quality of life based on property crime and temperature. The SVM and GBT models seem to perform relatively well in explaining the variability in property crime, with R^2 values of 0.67 and 0.66, respectively. It is noteworthy that despite its relatively low influence, Temperature still had a discernible effect on the quality-of-life predictions mainly in RF, GBT, and SVM. The low influence temperature in this analysis is in line with the Malaysia's tropical climate, where temperature variations may be relatively consistent throughout the year.

4. CONCLUSION

This research findings provide insight into the performance of various machine learning algorithms in predicting quality of life. The analysis not only evaluates the algorithm's predictive accuracy but also explores and examine into how the IV, property crime and temperature influence these algorithms. It demonstrates that the impact of IV can be context-dependent and that SVM is a strong candidate for accurate predictions in this research. SVM strong predictive capabilities and accuracy make it the preferred choice for predicting quality of life in this research. However, the selection of the suitable algorithm should always consider the broader context, including computational resources and interpretability requirements. However, it is essential to consider the context and the goals of the analysis when selecting the most appropriate model, as factors like model interpretability, computational resources, and other domain specific knowledge also play a role in choosing the right model. Future research in the field of quality-of-life prediction especially in relation to criminal activity and temperature offers several further works such as integrating diverse data sources, such as crime records, weather data, and geospatial information on the built environment, can lead to more holistic quality of life predictions. Combining these data types using advanced techniques like multi-model deep learning could enhance the accuracy of models. In addition, collaborating with urban planners and policymakers is critical to ensure that research findings are translated into actionable policies and intervention aimed at improving quality of life in specific areas. Develop decision supports systems that allow policymakers, urban planners, and local communities to interact with the models, explore "what-if" scenarios, and test the potential impact of different interventions.

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BIOGRAPHIES OF AUTHORS

Anis Zulaikha Mohd Zukri is a research assistant and postgraduate student in UiTM. Received bachelor's degree of Town and Regional Planning in 2021 from UiTM Selangor Branch. She is currently pursuing the M.Sc. in Built Environment with Universiti Teknologi MARA (UiTM) Perak Branch. Her current research interest in CPTED, safe cities, quality of life, and machine learning. Received the grant from the MOE in the areas of crime and the environment and safe cities for her research. She can be contacted at email: zulaikhazukri15@gmail.com.

Siti Rasidah Md Sakip is a senior lecturer at UiTM, with 20 years of experience in Landscape Architecture. She holds a Ph.D. in Crime and the Environment (2012) and an M.Sc. in Science Landscape Architecture (2002). She received her bachelor's degree in Interior Design from USM in 2000. She is the most active researcher at UiTM Perak, awarded from 2015 to 2023. Her research focuses on CPTED, safe cities, landscape architecture, and green development. She leads the Green Safe Cities Research Group and serves as chief editor of the Malaysian Journal of Sustainable Environment. She can be contacted at email: sitir704@uitm.edu.my.

Suraya Masrom is the head of the machine learning and interactive visualization (MaLIV) Research Group at UiTM Perak. She earned her Ph.D. in Information Technology and Quantitative Science from UiTM in 2015. She began her career as an Associate Network Engineer at Ramgate Systems in 1996 after obtaining her bachelor's degree from UTM. She became a lecturer at UTM in 2001 after earning her master's from UPM and joined UiTM in 2004. She is an active researcher in meta-heuristics, machine learning, and educational technology. She can be contacted at email: suray078@uitm.edu.my.