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CLIMATE-RESPONSIVE URBAN SAFETY: PREDICTIVE MODELLING OF TEMPERATURE-DRIVEN PROPERTY CRIMES FOR QUALITY OF LIFE

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Abstract

Understanding the relationship between temperature, crime, and quality of life is crucial for addressing urban challenges and fostering sustainable development. While community safety is a key focus of the Sustainable Development Goals (SDGs), the link between temperature, property crime, and quality of life remains underexplored. Most studies emphasize violent crimes, neglecting property crimes and their nuanced interactions with environmental factors. Additionally, the indirect effects of temperature and crime on quality of life lack sufficient investigation. This study addresses these gaps by analysing the relationship between temperature, property crime, and quality of life using machine learning techniques, including, Generalized Linear Model, Support Vector Machine, Gradient Boosted Tree, Decision Tree and Random Forest algorithms. Data were collected from 317 face-to-face surveys in Taman Dato' Senu, Sentul, Kuala Lumpur, alongside official crime statistics from the Royal Malaysia Police. Results indicate that property crime significantly influences quality of life, whereas temperature shows minimal direct impact. These findings highlight the complex dynamics between climate and social behaviour and demonstrate the potential of machine learning for precise, data-driven insights to support urban planning and policy decisions in tropical cities.

Keywords: Property crime, temperature, quality of life, machine learning

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INTRODUCTION

Urbanization, while driving economic growth, also creates challenges for sustainable development, requiring coordinated policies to address its adverse effects. The concept of quality of life, a cornerstone of national and international agendas like Agenda 21 and the Sustainable Development Goals (SDGs), emphasizes the holistic well-being of communities (Ali Haider & Iamtrakul, 2018). In Malaysia, development plans prioritize quality of life, balancing economic growth with societal welfare, environmental protection, and security. Safety and security, as vital components of quality of life, are highlighted in national initiatives such as the Twelve Malaysian Plan and Crime Prevention Through Environmental Design. Crime, a pressing social issue, poses significant risks to public safety, necessitating studies to explore its relationship with various factors.

While quality of life and crime have been extensively studied, including environment safety (Zyed, Harumain, Matsunaga, Hashim, & Azmi, 2025; Abd Ghany & Naharudin, 2025), the interplay between crime, temperature, and quality of life remains underexplored. Crime trends are associated with many factors, including, but not limited to, socio-economic conditions, social inequality and unemployment rates (Hakim et al., 2022). Previous research on quality of life has employed various indicators, such as health status (Tang et al., 2020), socioeconomic factors (Huguet et al., 2008), subjective well-being (Kinderman et al., 2011; Norman et al., 2000), and environmental conditions (Mouratidis, 2020). However, in urban geography and studies, the connection between temperature, crime, and quality of life has received limited attention (Kitchen & Williams, 2010).

This study seeks to address the research gap by examining how temperature variations influence property crime rates and their implications for urban quality of life, focusing on Malaysian cities where temperature differences are relatively small but environmentally significant. While Malaysia experiences minimal seasonal fluctuation, even modest increases in heat intensity, from 36°C to 40°C were expected to affect human comfort, health, and behaviour. To utilize a machine learning-based predictive framework enables this study to detect and model such subtle temperature and crime interactions with greater precision than conventional statistical methods. This approach contributes new empirical insights from a tropical urban context, extending international discussions that predominantly emphasize temperate regions.

RESEARCH BACKGROUND

Impact of Property Crime on Quality of Life

The fear of crime is a global issue affecting nearly every city. Both crime and the fear of crime are serious issues that must be addressed as they contribute to a

decreased quality of life (Sciences & Shamsuddin, 2013). Crime has psychological and physical impacts on everyone involved, including the victims, reducing their overall quality of life. This uneasiness in society is far from ideal for the social development of urban dwellers (Farhan Kamarulzaman, 2020). Ishak & Bani (2017) investigated the relationship between crime and the quality of urban geography and urban studies. However, few studies (Corcoran & Zahnnow, 2021; Ghani, 2017; Kitchen & Williams, 2010; Lynch et al., 2020; Soh, 2012; Trujillo & Howley, 2021) have examined the relationship between crime and quality of life.

The effect of crime on citizens' daily lives are numerous. Most of the costs incurred from criminal activities are direct and have immediate impact. Fear of crime, lower life satisfaction, psychological issues, lower quality of life, and non-monetary cost are all examples of indirect costs with long-lasting impact. From a theoretical perspective, understanding the dynamics of criminal activity is important because it sheds light on criminals' maximizing behaviour (Lersch & Hart, 2020).

Research on the fear of crime suggests it harms quality of life and psychological well-being (Ishak & Bani, 2017). Studies link crime, including its relationship with temperature, to widespread social concerns, emphasizing its impact on societal productivity and quality of life. Efforts to combat crime often divert time that could be more productively used to enhance well-being. Crime remains a global challenge with significant implications for urban quality of life (Ishak & Bani, 2017).

Domain of Quality of Life

The quality of life is classified into six (6) domains as seen in Table 1. Three (3) out of six (6) dimensions were chosen to be applied in this study, namely a) physical environmental, b) psychological, and c) social. Quality of life measures different elements. Measuring the quality of life from a physical environment aspect emphasizes elements that provide security, such as safety at home, in the neighbourhood areas, and the city.

Meanwhile, the measurement of quality of life for the psychological aspect emphasizes feelings of a fear, stress, and happiness. Therefore, to assess the influence of local criminal activity on people's quality of life, it is necessary to evaluate the respondents' psychological state. Next, the researcher focuses on the environmental aspects, which concentrate on weather elements such as temperature, based on the influence of temperature on criminal activity. Here, the researcher would assess how people perceive the impact of temperature on their quality of life in the context of criminal activity.

Table 1: The quality of life domains

Domain	References
Physical Environmental	(Bracy et al., 2014; Ghani, 2017; Mihinjac & Saville, 2019; Mohit, 2013b; Serag El Din, Shalaby, Farouh, & Elariane, 2013; Soh, 2012)
Mobility	(Bracy et al., 2014; Serag El Din et al., 2013)
Social	(Ghani, 2017; Mohit, 2013b; Soh, 2012)
Psychological	(Kitchen & Williams, 2010; Lersch & Hart, 2020; Mohit, 2013b; Serag El Din et al., 2013; Trujillo & Howley, 2021)
Economic	(Ghani, 2017; Serag El Din et al., 2013)
Political	(Ghani, 2017; Mohit, 2013a; Serag El Din et al., 2013; Soh, 2012)

Finally, the researcher looks at the social aspects to examine the relationship of people with their social activities based on the level of security around them. This section reviews the objective measures suggested in the literature for each identified quality of life domain category. The primary goal of this review is to find the related dimensions and criteria of each domain addressed in this research, from which preferable candidate indicators would be suggested for this study.

The Relationship Between Quality of Life and Crime and Temperature Changes

Understanding the relationship between crime, temperature, and quality of life requires thorough analysis. External factors like weather significantly influence behaviour, with studies highlighting how temperature fosters aggression and diminishes self-control (Ranson, 2014). Research on the weather-crime link began in the 1960s, revealing a notable impact of temperature on criminal behaviour. Scholars stress the importance of examining weather factors, as evidence shows a correlation between higher temperatures and increased crime rates, particularly violent offences. This highlights the critical role of temperature in explaining seasonal variations in violent crime (Jung et al., 2020).

Temperature significantly influences human behaviour, including the tendency to engage in criminal activity. Environmental factors such as temperature, rainfall, and wind conditions affect outdoor human activity, thereby influencing the likelihood of crimes such as assault and property theft. Research indicates that “pleasant” weather conditions may increase the opportunity for property crimes, whereas “unpleasant” weather tends to deter such activities (Horrocks & Menclova, 2011). Despite research on crime, temperature, and quality of life, significant gaps remain in understanding their combined impact on human well-being and life satisfaction (Ghani, 2017; Soh, 2012). Scholars have suggested that climate change may exacerbate aggression and violent

behaviour, highlights the need for further empirical investigation to clarify these dynamics and their broader societal implications (Habibullah, 2017).

Machine Learning in Quality of Life Prediction

As data accumulation grows exponentially, machine learning has become essential for intelligent analysis, outperforming traditional methods in handling complex information (Kim et al., 2019). In crime-prediction research, machine learning uses data-mining techniques to identify hidden patterns within large datasets, thereby assisting law-enforcement agencies in managing criminal incidents (Malathi & Baboo, 2011). Predictive models leverage variables such as time, weather, and location, and employ algorithms like K-Nearest Neighbours (K-NN) and decision trees to forecast criminal behaviour effectively (Bharati & Rak, 2018; Kim et al., 2019a; Wu, 2019). This study further explores the potential of machine learning by employing additional algorithms that have not yet been widely applied in temperature-related crime prediction.

RESEARCH METHODOLOGY

The research employs a quantitative methodology that integrates primary data collected through surveys with secondary data obtained from agencies, industries, and archival sources to gather and analyze relevant information for achieving its objectives (Sekaran & Bougie, 2016). Primary data was gathered through questionnaires, captures public perceptions of quality of life in relation to crime.

Temperature data were collected alongside the questionnaire survey to examine its potential influence on the study's key focus areas. Secondary data were sourced from the Royal Malaysia Police (RMP), encompassing ten years (2011–2020) of crime records. This crime data, drawn from monthly and yearly reports, is categorized into six offence types: theft, vehicle theft, motorcycle theft, lorry/van/truck theft, snatch theft, and burglary (PDRM, 2021).

Site Selection

The site selection process for this study involved several vital steps. The crime index from 2011 to 2020 was initially gathered from the RMP. Table 2 highlights Selangor, Kuala Lumpur, and Johor as regions with the highest crime rates in Malaysia. These three states represent highly urbanized areas where criminal behaviour tends to increase alongside rapid development and population density. The concentration of crimes in these regions highlight the need to examine the interaction between environmental stressors such as temperature and urban heat and social behaviour. This finding further justifies the study's focus on urban settings, where small variations in temperature can have amplified effects on human comfort, behaviour, and consequently, property crime incidence.

Table 2: The crime index statistics in Malaysia from 2011 to 2020

State	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Johor	20970	19068	17105	15082	13480	12941	11307	10338	9870	7350
Kedah	10667	10100	8636	8028	7817	7440	6759	6221	5615	4131
Kelantan	6199	6053	5737	5603	5031	4548	4520	3987	3545	2531
Kuala Lumpur	25002	23022	22319	18293	15946	16989	13482	12127	11172	8301
Melaka	4830	4764	4186	3675	2948	3664	3097	2800	2561	1794
Negeri Sembilan	6050	6563	5993	5495	4787	4474	3973	3673	3327	2431
Pahang	5994	5619	5257	5085	4257	3777	3607	3584	3271	2331
Perak	9869	8545	7429	6860	6228	5841	5326	5128	4912	3388
Perlis	1113	974	831	814	741	655	603	563	527	493
Pulau Pinang	9758	8399	7936	7491	6697	6116	5551	5017	5218	3853
Sabah	-	3489	5772	5210	5176	5367	6236	6151	5745	3799
Sarawak	-	6202	9191	7556	7230	6826	6381	5830	6023	5850
Selangor	44302	40629	43060	36165	32547	31222	26069	21420	19800	17272
Terengganu	3841	3505	3610	3213	2659	2494	2257	1823	1870	2099
Total	148595	146932	147062	128570	115544	112354	99168	88662	83456	63524

Source: Royal Malaysia Police, (2021)

Crime is divided into six types: theft, vehicle theft, motorcycle theft, lorry/van/truck theft, snatch, and burglary. Details of the index crime categories are shown in Table 3.

Table 3: Property crime data in Johor, Kuala Lumpur, and Selangor

State	Year	Theft	Vehicle Theft	Motorcycle Theft	Lorry/Van/Truck Theft	Snatch	Burglary
Johor	2011	3811	2006	7571	479	76	2598
	2012	2910	1738	7731	590	38	2219
	2013	2322	2188	6754	776	28	1798
	2014	2216	1686	6052	552	40	1603
	2015	1934	1592	5595	473	33	1440
	2016	2073	1443	4686	400	44	1475
	2017	2032	1097	4104	274	11	1211
	2018	2021	1035	3881	278	4	1239
	2019	1908	981	3471	219	4	1364
	2020	1403	802	2347	141	0	1273
Kuala Lumpur	2011	4497	3326	5692	664	951	3480
	2012	3910	3359	5693	549	384	2838
	2013	3391	3281	5459	688	214	2506
	2014	3133	2481	4469	548	593	2118
	2015	2995	2229	4015	524	604	1907
	2016	3595	2104	3864	495	1288	1867
	2017	3121	1548	3328	291	7	1188
	2018	3118	1482	3030	253	3	1104
	2019	2729	1423	2763	254	2	1087
	2020	2057	1000	2200	147	0	949

Selangor	2011	5941	6389	12957	1653	799	8422
	2012	4437	5792	13285	1757	725	6337
	2013	5147	5832	12653	2049	984	7742
	2014	4675	4723	10688	1648	845	6184
	2015	4157	3932	9794	1326	950	5805
	2016	4793	3309	8890	1140	983	5497
	2017	3951	2586	7945	844	140	4133
	2018	3638	2358	6510	654	87	3515
	2019	3514	2204	5503	595	3	3679
	2020	3753	1544	4337	374	0	3025

Source: Royal Malaysia Police, (2022)

Despite Selangor exhibiting the highest property crime statistics, Kuala Lumpur was ultimately chosen due to its second-highest crime rate in Malaysia, logistical ease in data collection, and the constraints faced in unsuccessfully accessing data from Police Headquarters Petaling Jaya, Selangor. Table 4 shows Brickfields, Cheras, Dang Wangi, Sentul, and Wangsa Maju for the property crime statistics in Kuala Lumpur.

Table 4: Statistic of property crime in Kuala Lumpur district from 2011 to 2021

Year	Brickfields	Cheras	Dang Wangi	Sentul	Wangsa Maju	Total
2011	4574	4965	2952	5740	0	18231
2012	3958	3737	3202	5507	0	16404
2013	3133	3374	3031	5668	0	15206
2014	2458	2525	2679	3533	1854	13049
2015	2304	2126	2587	2783	2228	12028
2016	2145	2041	3311	2698	2755	12950
2017	1441	1470	2254	2063	2019	9247
2018	1497	1370	2162	1850	1916	8795
2019	1492	1258	1649	2005	1631	8035
2020	1212	1030	1364	1407	1220	6233
2021	752	806	1034	1162	881	4635
Total	24966	24702	26225	34416	14504	124813

Source: Royal Malaysia Police, (2022)

Further analysis of crime data within Kuala Lumpur pinpointed Sentul as the area with the highest crime rate, as shown in Table 4. Sentul was situated within the administrative division of Mukim Batu, which was characterized by its division into Sentul West and Sentul East. It features various residential types, focusing on landed residences for this study. The site selection process culminated in the Taman Dato' Senu as the study area, driven by statistical evidence indicating its heightened crime rates compared to neighbouring areas and its composition of one-storey and two-storey landed housing, particularly terrace houses, which lacked security measures (refer Figure 1).

This study used the random systematic sampling method to determine the selection of residents with the 317-sample size. In this preliminary study, 317 samples were reached to cover all subgroups of the target population (Han et al.,2018). The questionnaire was used to collect the data that comprises of quality of life, domains. The section of questionnaire was developed based on the three constructs of the quality of life: physical environment, psychological, and social. Each construct was measured using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree), with estimates derived from the average scores of their indicators.

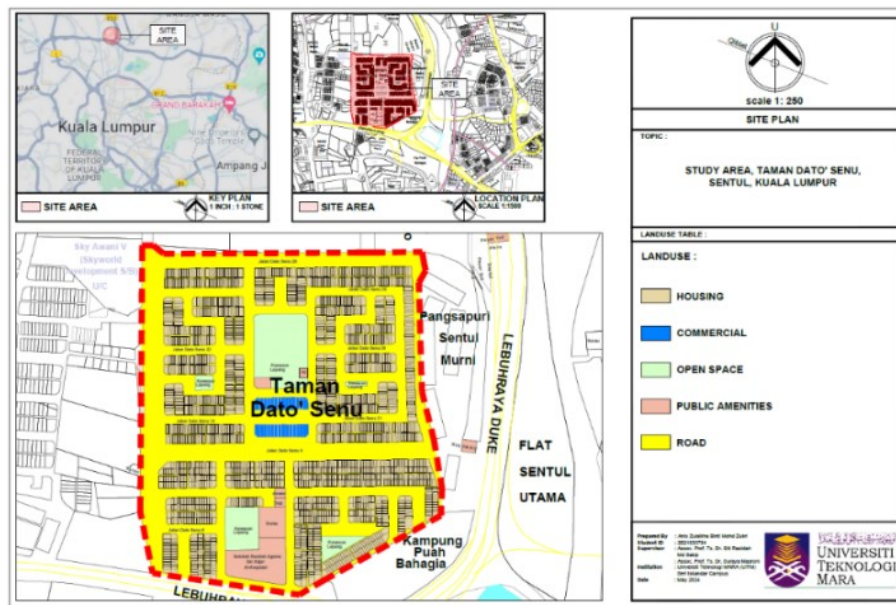


Figure 1: Study area in Taman Dato' Senu, Sentul, Kuala Lumpur

The questionnaire was conducted face-to-face with residents of Taman Dato' Senu, Sentul, Kuala Lumpur, ensuring clarity and adherence to survey instructions. Of 317 questionnaires distributed, 254 valid responses were collected, achieving an 80% response rate. Temperature data in degrees Celsius (°C) was recorded on each form using a smartphone during the survey process.

DATA ANALYSIS AND RESULT

Correlation Analysis

The Pearson correlation coefficient results in Table 5 shows the relationship between property crime and temperature changes towards quality of life.

Table 5: Pearson correlation coefficient result

	Property crime	Quality of life	Temperature
Property crime		0.726**	0.097
Quality of life	0.726**		0.057
Temperature	0.097	0.057	

**Correlation is significant at the 0.01 level (2-tailed)

Based on the Table 5, the analysis shows a Pearson correlation coefficient ($r=0.726$) between property crime and quality of life, with a ($p=0.01$), indicating that this relationship is statistically significant. This means that property crime rate has a noticeable impact on quality of life, affecting factors like the physical environment, psychological, and social. Meanwhile, the relationship between the variable temperature, quality of life and property crime is not statistically significant with p value above 0.005. The analysis highlights a significant correlation between property crime and quality of life. In contrast, the influence of temperature on quality of life appears to be minimal and not statistically significant. The Pearson correlation result in Table 6 shows the relationships between property crime and the three quality of life domains (physical environment, psychological, and social).

Table 6: Pearson correlation coefficient result

	Property crime	Physical Environment domain	Psychological domain	Social domain
Property crime		0.998**	0.351**	0.140*
Physical Environment domain	0.998**		0.349**	0.148*
Psychological domain	0.351**	0.349**		0.003
Social domain	0.140*	0.148*	0.003	

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

The analysis of correlation coefficients shows relationships between property crime and different domains of quality of life. Firstly, the exceptionally strong positive correlation between property crime and the physical domain ($r=0.998$, $p<0.01$) indicates that as property crime increase, there is a substantial deterioration in the quality of life of the physical environment.

Additionally, a moderate positive correlation is observed between property crime and the psychological domain ($r=0.351$, $p<0.01$). This indicates that higher property crime is associated with an increase in psychological distress among the community members. The people would get more chances for fear and stress if property crime increase due to concern about their safety. Furthermore,

a statistically significant but it shows slightly as the correlation is found between property crime and social domain ($r=0.140$, $p<0.05$). This indicates that while higher property crime may impact social patterns within the community.

Machine Learning

This research presents two distinct sets of results. Firstly, Table 7 outlines the performance outcomes of machine learning in predicting the quality of life. This table can compare each machine learning algorithm's performance using the two feature selections. Secondly, Figure 2 presents an in-depth presentation and discussion of how machine learning algorithms are influenced by two independent variables: 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 independent variables.

Table 7: The performances of result

Algorithm	RMSE (+/- std dev)	R [^] (+/- std dev)	Time to Complete (s)
Feature Selection 1			
Generalized Linear Model	0.345(+/-0.056)	0.612(+/-0.205)	9
Random Forest	0.32 (+/-0.067)	0.626(+/- 0.261)	1
Decision Tree	0.327(+/-0.038)	0.654(+/-0.211)	5
Gradient Boosted Trees	0.367(+/-0.069)	0.568(+/-0.238)	84
Support Vector Machine	0.339(+/-0.064)	0.666(+/-0.294)	76
Feature Selection 2			
Generalized Linear Model	0.345(+/-0.056)	0.612(+/-0.205)	0.838
Random Forest	0.32 (+/-0.039)	0.613(+/- 0.307)	0.243
Decision Tree	0.344(+/-0.038)	0.538(+/-0.332)	4
Gradient Boosted Trees	0.384(+/-0.067)	0.472(+/-0.365)	87
Support Vector Machine	4.363(+/-0.025)	0.684(+/-0.094)	44

Although temperature exhibits a low correlation according to the Pearson test when considered outside machine learning algorithms, its utility in enhancing predictive abilities becomes apparent within specific algorithms. Despite the initial low correlation value, temperature contributes valuable insights to specific algorithms, leading to improved 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 essential and improve prediction results. Regarding predictive accuracy, the root means square error (RMSE) measures how close the model's predictions are to the actual values. Lower RMSE values indicate better predictive performance. Among the algorithms, the Decision Tree exhibited the lowest RMSE of 0.32 (+/- 0.067), followed closely by Random Forest 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 data. A higher R^2 value indicates better alignment between predictions and actual values. In this case, Support Vector Machine 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 , the Support Vector Machine emerges as the best-performing algorithm in predicting quality of life. The higher R^2 and competitive RMSE indicate robust predictive capabilities and accurate results. Support Vector Machine outperformed other algorithms in this study primarily due to its strength in handling non-linear relationships between temperature variables and property crime rates. Unlike linear models such as Generalized Linear Model, which assume a direct linear correlation, Support Vector Machine can map complex data relationships through kernel functions, allowing it to capture subtle interactions that may exist between climatic variations (small temperature differences between 36°C and 40°C) and crime patterns.

However, practical considerations such as computational time should also be considered when selecting the most suitable algorithm for a specific use case. Support Vector Machine took longer than Generalized Linear Model, Random Forest, and Decision Tree. Nevertheless, the time taken is considerably acceptable, 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 each machine learning algorithms.

Based on Figure 2 illustrate the comprehensive framework guides researcher through a series of sequential of steps, commencing from the establishment of initial research goals to the thoughtful selection of a machine learning tailored for predicting quality of life. The process is initiated by undertaking systematic literature review and correlation analysis, followed by feature selection using various machine learning algorithms for subsequent phases.

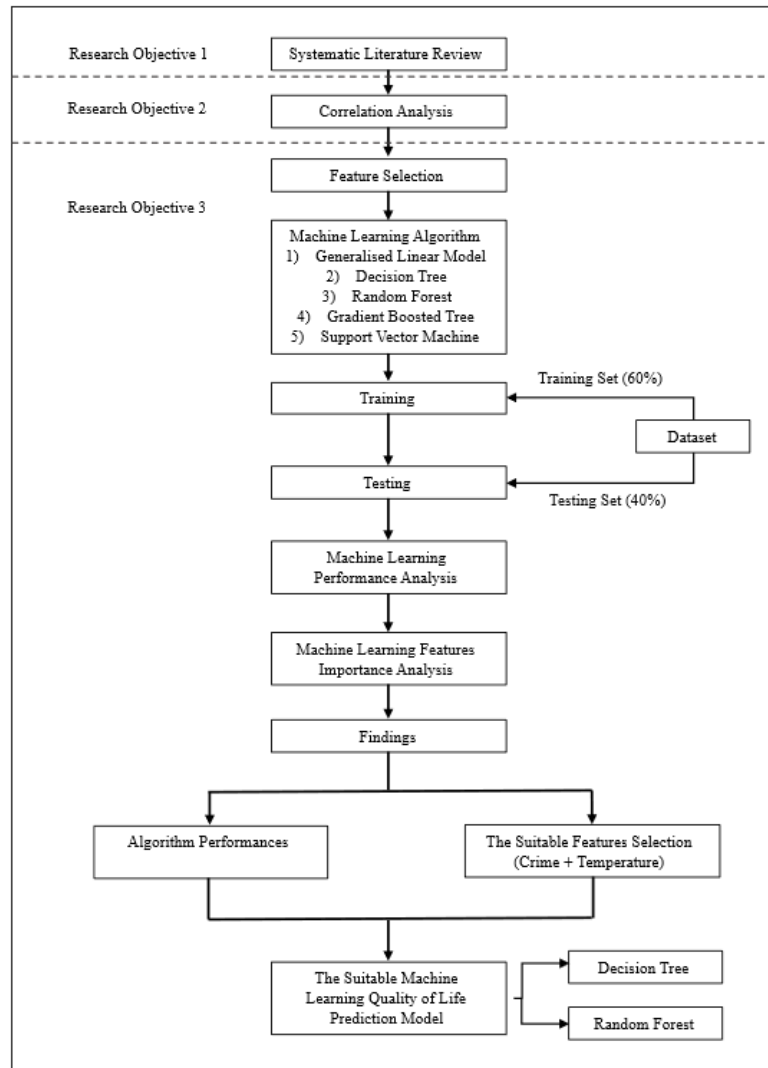


Figure 2: The suitable machine learning quality of life prediction model framework

A crucial of the framework is the feature selection phase, where a diverse array of machine learning algorithms is utilized. The selected algorithms assume a central role in the ensuing “Training” phase, where the “Training Set (60%)” dataset is utilized to refine and optimize the chosen features. Subsequently, a critical “Testing” phase ensues, subjecting the features to evaluation using the “Test Set (40%)” dataset.

The outcome of this thorough testing analysis results in two essential analyses: the “Machine learning Performance Analysis” and the “Feature Importance Analysis”. These analyses serve as vital pathway leading to the subsequent phase of formulating “Findings”. Within the findings, the framework incorporates a thoughtful evaluation of “Algorithm Performances”, concluding in the identification of “The Suitable Features Selection”. This insight serves as the keystone for the final section of the framework, wherein researcher thoroughly select a suitable machine learning model for predicting quality of life.

DISCUSSION AND CONCLUSION

This study finds no significant relationship between property crime and temperature, aligning with prior research showing temperature impacts violent crime but not property crime. Scholars like Corcoran & Zahnow (2021) suggest that property crime is less influenced by environmental factors, emphasizing the need to explore alternative variables such as socioeconomic conditions, urban density, and opportunity structures. Malaysia’s tropical climate, with relatively stable temperatures, may explain the lack of temperature’s impact on crime compared to regions with extreme seasonal changes.

Despite this, the study contributes by linking property crime to quality of life across physical, psychological, and social domains, highlighting how fear of crime and perceptions of safety influence well-being. Using machine learning techniques like Decision Tree and Random Forest, the study advances traditional methods, uncovering complex relationships between temperature, crime, and quality of life.

Future research should explore other environmental factors, urban design, and socioeconomic inequalities, and conduct comparative studies across diverse climates. Advanced computational tools, such as machine learning, offer potential for better predictive models, informing policies that enhance safety, security, and quality of life, while supporting Sustainable Development Goals related to urban sustainability and social equity.

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