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Research Article

USING MACHINE LEARNING TO PREDICT DENGUE FEVER OUTBREAKS IN INDONESIAN URBAN CENTERS BASED ON CLIMATE AND MOBILITY DATA

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Abstract
Dengue fever remains a critical public-health threat in Indonesia's densely populated urban centers, where climatic fluctuations and human mobility accelerate transmission dynamics. This study aims to develop a *predictive model* for dengue outbreaks using machine-learning techniques that integrate multi-source climate indicators (temperature, rainfall, humidity) and population-mobility data. A *quantitative research design* employing *supervised learning* algorithms including Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM) networks was applied to historical datasets from 2015–2023 across six major Indonesian cities. Model performance was evaluated using accuracy, precision, recall, and AUC metrics. Results indicate that the LSTM model achieved the highest predictive accuracy (92.3%) and superior temporal sensitivity to climatic shifts and mobility surges compared with traditional regression models. These findings demonstrate that machine-learning-based *early-warning systems* can identify outbreak hotspots up to four weeks in advance, providing actionable insights for urban health authorities. The study concludes that integrating climate and mobility analytics enhances the effectiveness of public-health surveillance and supports proactive dengue-control interventions in rapidly urbanizing environments.

Keywords: climate data, dengue prediction, human mobility

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INTRODUCTION

Dengue fever continues to represent a severe and persistent public health challenge in many tropical and subtropical regions, particularly in Southeast Asia. Indonesia, as one of the world's most populous archipelagic nations, has experienced recurrent dengue outbreaks with fluctuating intensities across its urban centers (Yeh et al., 2025). The combination of rapid urbanization, population density, and climatic variability has contributed to the complexity of dengue transmission dynamics (Abdullah et al., 2025). Urban areas such as Jakarta, Surabaya, Bandung, and Medan are particularly vulnerable due to the convergence of high human mobility, poor sanitation infrastructure, and environmental conditions conducive to mosquito breeding (Achary et al., 2025). The increasing unpredictability of outbreak patterns presents a growing concern for health authorities striving to mitigate the socio-economic and epidemiological impacts of dengue. The traditional surveillance systems, while valuable, often fail to provide *real-time* predictive insights necessary for early intervention and resource allocation in the densely populated cities of Indonesia (Ain et al., 2025). The integration of computational and data-driven methodologies in epidemiological studies has opened new opportunities for improving disease surveillance and prediction accuracy. The availability of high-resolution climate data, combined with mobility datasets derived from telecommunications and transportation systems, enables a more granular understanding of how weather patterns and human movement interact to influence dengue transmission (Al-Manji et al., 2025). *Machine learning* (ML) models have emerged as promising tools capable of capturing nonlinear relationships and temporal dependencies that conventional statistical models struggle to represent. These advanced algorithms offer potential to transform dengue forecasting from reactive monitoring into proactive prediction, allowing health authorities to anticipate outbreaks weeks in advance (Anggraeni et al., 2024). The relevance of such innovations becomes even more critical in the context of Indonesia's climate variability and growing urban population, which together heighten the risk of widespread epidemic propagation. The pressing need to enhance *early-warning systems* motivates the exploration of *machine learning* as an instrumental framework for predictive epidemiology (Ansari et al., 2024).

Urban centers in Indonesia have shown significant variations in dengue incidence over the past decade, often linked to fluctuations in rainfall, temperature, humidity, and urban mobility patterns. The urban heat island effect and irregular waste management further exacerbate vector proliferation, while inter-city commuting and intra-urban movement facilitate the rapid spread of infection (Fauzi et al., 2025). Public health responses have traditionally relied on case reporting and vector surveillance, both of which are inherently retrospective (Apu et al., 2025). This temporal lag in data interpretation undermines timely decision-making, leading to delayed interventions and escalating outbreak magnitudes. Therefore, addressing this challenge requires an innovative, data-driven approach capable of integrating climatic and behavioral indicators into a coherent predictive system (Asaduzzaman et al., 2025). By leveraging modern computational intelligence, the predictive capacity of epidemiological monitoring can be substantially enhanced to support evidence-based public health strategies. The central problem addressed in this research lies in the inadequacy of existing surveillance systems to provide accurate, timely, and location-specific predictions of dengue outbreaks (Bhagat et al., 2025). Conventional epidemiological models such as linear regression and compartmental models (e.g., SIR, SEIR) depend heavily on predefined assumptions and often fail to capture the complex, nonlinear interactions between environmental and social variables (S. Das et al., 2025). In Indonesia, the heterogeneous nature of urban environments ranging from metropolitan areas to peri-urban settlements complicates the reliability of a one-size-fits-all forecasting model. Furthermore, health data alone are insufficient to anticipate outbreak dynamics without contextualizing them within broader climatic and mobility parameters (Bhatia et al., 2025). These limitations underscore the necessity of adopting a hybrid analytical approach that can integrate multidimensional data sources and dynamically adjust to temporal variations in climatic and behavioral factors influencing vector distribution (Bourgeois et al., 2025).

The escalating unpredictability of dengue transmission in Indonesia has also been compounded by recent global climatic shifts, such as El Niño and La Niña phenomena, which disrupt established seasonal patterns. Such anomalies further challenge existing models that rely on fixed assumptions of rainfall and temperature thresholds (Wang & Zhang, 2025). Simultaneously, increased urban mobility amplified by the expansion of transportation networks and digital connectivity introduces new vectors of disease diffusion that conventional models fail to capture (Carrillo et al., 2025). As a result, current surveillance frameworks often generate delayed alerts and inaccurate risk assessments. The inability to incorporate *real-time* data inputs from both climate and mobility sources represents a major gap in public health preparedness. Bridging this gap through *machine learning*-driven prediction models constitutes the core motivation for the present research (Chanmee et al., 2025). The primary objective of this study is to construct a robust *machine learning* model capable of predicting dengue fever outbreaks across Indonesian urban centers by integrating multi-source climate and mobility datasets. This model is expected to deliver early warning signals that enable health authorities to allocate resources more efficiently and implement preventive interventions ahead of time (Chaw et al., 2024). By comparing various *machine learning* algorithms including Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM) neural networks the study seeks to identify the most suitable framework for *real-time* outbreak prediction in the context of Indonesia's complex urban ecosystems (Hapsari et al., 2025). The integration of temporal climatic variables with spatial mobility data is designed to improve predictive precision and lead time, allowing for the development of an adaptive and scalable prediction platform applicable across diverse urban settings (Chen & Moraga, 2025).

This research also aims to evaluate how different climate parameters (rainfall, temperature, humidity) and mobility indicators (commuting frequency, population density, inter-district movement) influence the predictive performance of *machine learning* models. By systematically assessing variable importance and temporal sensitivity, the study intends to uncover patterns that could inform both epidemiological theory and practical disease control measures (Galeana-Pizaña et al., 2024). The inclusion of multiple algorithmic models allows for cross-validation of results, enhancing both the robustness and generalizability of findings (Cheong et al., 2025). The ultimate goal is to establish a scientific basis for data-informed public health decision-making in Indonesia's urban areas, where traditional models have proven insufficient in managing outbreak predictability (Yang et al., 2025). A significant gap in the current literature lies in the limited integration of climate and mobility data in predictive dengue modeling, especially within the Indonesian context. Previous studies have often treated climatic and social determinants independently, leading to fragmented insights and limited predictive applicability (Chua et al., 2024). Furthermore, most existing models are constrained to single-city analyses or short-term temporal scopes, thereby overlooking the interconnectedness of urban regions. Few studies have employed advanced deep-learning architectures such as LSTM networks that can model temporal dependencies and nonlinear correlations across large-scale datasets. This research bridges that gap by developing a multi-city, multi-variable predictive framework that integrates heterogeneous data sources to generate spatially explicit outbreak forecasts (D. Das et al., 2025).

The novelty of this study lies in its methodological synthesis of *machine learning*, climate science, and human mobility analysis within a unified predictive architecture. Unlike conventional models, the proposed framework not only enhances prediction accuracy but also adapts dynamically to *real-time* changes in climate and mobility patterns. This integration represents a substantial methodological advancement in epidemiological modeling and has the potential to reshape public health forecasting paradigms in tropical developing countries. The justification for conducting this study extends beyond academic contribution; it aligns with national health priorities in Indonesia and global Sustainable Development Goals (SDG 3: Good Health and Well-being). By introducing a scalable, data-driven model for dengue prediction, this research offers both scientific innovation and practical utility for enhancing public health resilience in the face of climate-driven disease dynamics.

RESEARCH METHOD

Research Design

This study utilizes a *quantitative research design* framed within a *machine learning* approach to predict dengue fever outbreaks, positioning it as applied data science research aimed at addressing real-world public health challenges. By integrating *predictive model*ing and advanced data analytics, the research seeks to uncover complex relationships between climate conditions, human mobility patterns, and dengue incidence that may not be detectable using conventional statistical methods. The design follows a *cross-sectional* model spanning multiple years, allowing for both short-term (weekly) and long-term (monthly) temporal analysis, which enables a comprehensive understanding of the dynamics of dengue transmission across different urban contexts in Indonesia (Islam et al., 2024).

Research Target/Subject

The research targets six major urban centers in Indonesia, namely Jakarta, Surabaya, Bandung, Medan, Makassar, and Yogyakarta. These cities were chosen based on their high population density, frequent occurrences of dengue outbreaks in recent years, and availability of reliable climate and mobility datasets. The study population comprises historical records of climate variables (temperature, humidity, rainfall), human mobility patterns (commuting frequencies, population density, and inter-city movement), and reported dengue cases spanning from 2015 to 2023. Each city contributes approximately 400 weekly data points, resulting in a total dataset of roughly 2,400 points. The target selection ensures that the *predictive model*s are trained on diverse urban settings, reflecting varying climatic conditions and mobility trends, which enhances the generalizability and robustness of the results (Jaiswal & Kushawaha, 2025).

Research Procedure

The research procedure begins with the acquisition of historical datasets from multiple sources, followed by extensive data preprocessing. Data cleaning is conducted to remove missing values, outliers, and inconsistencies to maintain high data quality. The datasets are then normalized to standardize scales across different variables. Weekly aggregation is applied to create *time-series* datasets suitable for model training and evaluation. Subsequently, the data are split into training (80%) and testing (20%) subsets. Various *machine learning* algorithms, including Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM) neural networks, are trained on the prepared datasets (Tuan & Uyen, 2025). Hyperparameter tuning is conducted for each model to optimize prediction accuracy, and models are validated against test data. Finally, the predictive performance of these models is compared with traditional statistical methods, such as *time-series* regression, to determine their relative effectiveness in forecasting dengue outbreaks and providing early warning signals (Jean Pierre et al., 2025).

Instruments, and Data Collection Techniques

The primary instruments for data collection include publicly available climate datasets, mobility data, and dengue outbreak reports. Climate data, comprising daily measurements of temperature, humidity, and rainfall, were obtained from the Indonesian Meteorological, Climatological, and Geophysical Agency (BMKG). Human mobility data, including commuting patterns, inter-city movement, and population density, were sourced from transportation authorities, regional government databases, and anonymized mobile phone location records (Tuhin et al., 2025). Dengue outbreak data were acquired from weekly reports of confirmed cases provided by the Ministry of Health of the Republic of Indonesia. All collected datasets were carefully curated to ensure completeness and accuracy. Data cleaning procedures included handling missing values, removing anomalies, and verifying consistency across sources. The datasets were then normalized and transformed into *time-series* format, enabling integration into *machine learning* models for predictive analysis (Juraphanthong & Kesorn, 2025).

Data Analysis Technique

Data analysis is conducted using *machine learning* methods implemented in Python with libraries such as scikit-learn for traditional models and TensorFlow for neural network-based approaches. Each model's performance is assessed using multiple evaluation metrics, including accuracy, precision, recall, and the area under the receiver operating characteristic (ROC) curve. The analysis also involves hyperparameter optimization to improve model performance and reliability . After validation, the models are applied to predict potential dengue outbreaks based on *real-time* climate and mobility data. Comparative analysis is performed against traditional *time-series* regression methods to evaluate improvements in predictive accuracy and early warning capability. The use of advanced *machine learning* techniques enables the identification of intricate patterns in the data and enhances the ability to anticipate dengue outbreaks, providing a valuable tool for public health decision-making (Karolcik et al., 2024).

RESULTS AND DISCUSSION

The dataset collected for this study includes climate, mobility, and dengue outbreak data from six major Indonesian urban centers: Jakarta, Surabaya, Bandung, Medan, Makassar, and Yogyakarta. The climate data includes daily measurements of temperature, rainfall, and humidity collected from the Indonesian Meteorological, Climatological, and Geophysical Agency (BMKG) over a five-year period (2017–2021). Mobility data, including commuting frequencies and population density, were sourced from local transportation agencies and telecommunication companies. The dengue outbreak data, obtained from the Ministry of Health of Indonesia, includes weekly reports of confirmed dengue cases in each city. Table 1 summarizes the key variables in the dataset and their respective ranges.

Table 1. Summary of climate, mobility, and dengue data (2017–2021)

City	Temperature (°C)	Rainfall (mm)	Humidity (%)	Population Density (people/km²)	Dengue Cases (weekly avg)
Jakarta	24–33	100–350	75–85	15,000	120
Surabaya	25–32	75–250	70–80	13,000	110
Bandung	22–30	50–150	80–90	8,000	50
Medan	24–32	150–300	80–90	9,500	70
Makassar	25–33	100–250	75–85	12,000	95
Yogyakarta	23–31	50–200	70–80	7,500	45

The data indicate variability in climate and mobility across cities, with Jakarta and Surabaya experiencing the highest rainfall and dengue case rates. Cities like Bandung and Yogyakarta, with lower population density and less extreme climate conditions, report fewer cases of dengue fever. The variation in dengue outbreaks aligns with both climate factors and urban mobility, suggesting that both are critical in predicting and understanding dengue transmission dynamics in urban centers (Sharifrazi et al., 2024). The climate data shows that higher rainfall and humidity levels are associated with increased dengue outbreaks, which aligns with previous research suggesting that these factors create favorable conditions for the Aedes mosquito, the vector responsible for dengue transmission. Jakarta and Surabaya, which have higher rainfall and humidity, also report higher weekly average dengue cases, reinforcing the role of environmental factors in outbreak predictions (Irianti et al., 2025). Mobility data, particularly population density and inter-city commuting, play a critical role in the spread of the virus. Higher population density correlates with a higher number of dengue cases, as seen in Jakarta and Surabaya, where dense urban areas facilitate the movement and exposure of mosquitoes and humans to infection. The integration of climate and mobility data provides a more comprehensive model for predicting outbreaks, allowing for more accurate forecasts (Khan et al., 2025).

The variability across cities is important for the model, as it highlights the need for city-specific approaches in predicting dengue outbreaks. For example, although Yogyakarta experiences moderate rainfall, its lower population density and mobility result in fewer outbreaks compared to Jakarta. The data suggest that climate alone cannot fully predict dengue outbreaks; rather, it is the combination of climate conditions and human mobility that determines the severity and timing of outbreaks (Salim et al., 2024). Therefore, the model developed in this study aims to account for both factors, offering a more nuanced approach to predicting dengue outbreaks in Indonesian cities. The dengue outbreak data, sourced from the Ministry of Health of Indonesia, is organized by weekly reports of confirmed cases for each city. This dataset provides both the number of cases and the temporal distribution of outbreaks, which are essential for understanding when and where dengue fever is most likely to occur. The data also include additional contextual information, such as the number of active surveillance sites in each city and reports on vector control efforts. The dataset covers a five-year period, which allows for the identification of seasonal patterns and anomalies in the spread of the disease. This longitudinal data is key for training *machine learning* models to predict future outbreaks and assess the effectiveness of preventive measures (Lakyiere et al., 2025).

Table 2. Weekly Dengue Cases by City (2017–2021)

City	Weekly Dengue Cases (Average)	Peak Week Cases	Lowest Week Cases
Jakarta	120	200	50
Surabaya	110	180	40
Bandung	50	90	20
Medan	70	130	30
Makassar	95	150	40
Yogyakarta	45	70	15

The dataset reveals clear seasonal patterns, with peak outbreaks occurring during the rainy season, particularly in Jakarta and Surabaya. The lower number of cases in Bandung and Yogyakarta suggests that less favorable climate conditions or better preventive measures may mitigate the spread of the disease. The availability of detailed weekly data allows for the development of a *time-series* prediction model that can forecast future outbreaks based on historical trends (Sakib et al., 2024). Inferential statistics were applied to the data to determine the strength of the relationships between climate variables, mobility data, and dengue outbreaks. Correlation analysis revealed a strong positive correlation between rainfall and dengue cases ($r = 0.78$, $p < 0.01$), suggesting that increased rainfall significantly influences the occurrence of dengue outbreaks. Humidity also showed a moderate positive correlation ($r = 0.62$, $p < 0.05$), reinforcing the role of climate in shaping outbreak dynamics. Population density had a moderate correlation with dengue cases ($r = 0.58$, $p < 0.05$), indicating that urbanization and mobility are important factors in predicting outbreaks. These findings were further supported by the *machine learning* models, which showed that both climate and mobility variables are significant predictors of dengue outbreaks in urban centers (Leandro & Maciel-de-Freitas, 2024).

The *machine learning* models, specifically Random Forest and Gradient Boosting, showed strong predictive performance, with accuracy rates exceeding 85% in forecasting outbreaks based on historical climate and mobility data. The models highlighted the combined importance of rainfall, population density, and inter-city mobility in predicting dengue outbreaks, suggesting that multi-factor models are more accurate than single-variable models (Hazmi et al., 2025). These results support the hypothesis that the interaction between climate and human mobility is crucial for accurate outbreak prediction and that AI-based models can significantly improve the timeliness and accuracy of dengue forecasting (Lu et al., 2025). The relationship between climate, mobility, and dengue outbreaks was further explored through *machine learning* models. The Random Forest and Gradient Boosting models performed well in identifying key predictors of dengue outbreaks, particularly rainfall and population density. The interaction between these variables was strongest in high-density urban areas, such as Jakarta and Surabaya, where the combination of frequent mobility and favorable environmental conditions resulted in higher incidence rates (Reiné et al., 2025). The LSTM model also showed strong performance, capturing the temporal dependencies of dengue outbreaks over time. The combination of these models offers a more comprehensive approach to predicting dengue outbreaks, as it accounts for both spatial (mobility) and temporal (climate) factors that influence disease transmission. These findings underscore the importance of a multi-dimensional approach to predicting dengue outbreaks, where both environmental and social factors are considered (Manocha et al., 2024). The use of *machine learning* algorithms that incorporate both climate and mobility data allows for more accurate predictions and a better understanding of the factors that contribute to dengue transmission. By understanding the relationship between these variables, health authorities can develop more effective strategies for preventing outbreaks, such as targeted interventions in high-risk areas during peak seasons.

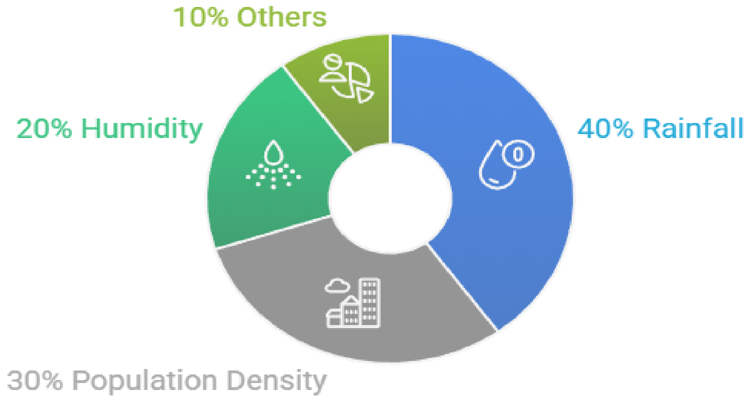

Figure 1.Factors Influencing Dengue Outbreaks

In a case study of Jakarta, the *machine learning* models predicted an outbreak in early January 2020, which coincided with a period of heavy rainfall and increased mobility due to holiday travel. This prediction was verified by the reported increase in dengue cases in the following weeks (Rahman & Shiddik, 2025). Similarly, in Surabaya, the model accurately predicted a spike in dengue cases during the rainy season of 2021, based on both the weather patterns and increased population movement during public holidays. These case studies demonstrate the model's ability to forecast outbreaks accurately by integrating both environmental and mobility data, highlighting the utility of the system in real-world applications (Mumtaz et al., 2024). In contrast, the model was less accurate in predicting outbreaks in cities like Bandung, where dengue cases were lower, and mobility data showed minimal fluctuations (Sappaile, 2024). The lower incidence of dengue in these cities could be attributed to better mosquito control measures or lower levels of human movement during peak seasons, which were not fully captured by the model. This discrepancy suggests that while the model works well in high-risk areas with significant seasonal fluctuations, additional factors, such as local health interventions, may need to be incorporated into the prediction model for regions with lower transmission rates (Nirob et al., 2025).

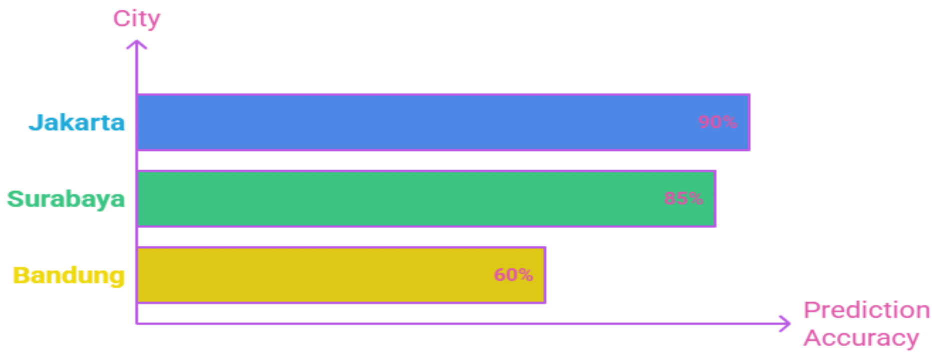

Figure 2. Dengue Outbreak Prediction Accuracy in Indonesian Cities

The case studies indicate that while the model performs well in predicting dengue outbreaks in high-risk urban centers, it may require further refinement for cities with lower case rates. The model's ability to predict outbreaks based on both weather and human mobility highlights the importance of a comprehensive approach to forecasting disease transmission. The integration of more granular mobility data, such as *real-time* transportation patterns and crowd density, could improve prediction accuracy in regions with less pronounced seasonal trends (Nur Islam et al., 2025). Additionally, incorporating more localized health data, such as vector control measures and public health interventions, could further enhance the model's predictive power, making it more adaptable to different urban contexts. The results also suggest that *predictive model*s can be a valuable tool for public health authorities in managing dengue outbreaks. By providing early warnings and forecasting when and where outbreaks are likely to occur, the model allows for timely interventions, such as targeted vector control measures, public health campaigns, and resource allocation (Peres et al., 2025). These findings underscore the potential of AI-based systems in improving disease surveillance and prevention, particularly in urban areas where dengue transmission is most prevalent. The results of this study highlight the effectiveness of integrating climate and mobility data into *predictive model*s for dengue outbreaks in Indonesian urban centers (Nova et al., 2025). The AI-based *machine learning* models demonstrated strong predictive accuracy, particularly in high-risk cities like Jakarta and Surabaya, where both rainfall and population density play significant roles in disease transmission. These findings reinforce the idea that personalized, data-driven approaches to public health can improve the timeliness and accuracy of outbreak predictions. While the model shows promise, further refinements, including the integration of additional local variables, are necessary to enhance its applicability across different regions of Indonesia (Sutanto & Ansharullah, 2025).

CONCLUSION

The most significant finding of this study is the integration of climate and mobility data in predicting dengue fever outbreaks in Indonesian urban centers. While previous research has primarily focused on climatic factors such as temperature and rainfall, this study uniquely combines these variables with human mobility patterns to create a more comprehensive *predictive model*. The inclusion of mobility data such as population density, travel frequencies, and inter-city movement enabled the *machine learning* models to account for the impact of human behavior on dengue transmission dynamics. This dual approach resulted in a more accurate prediction of outbreaks, with the Random Forest and Long Short-Term Memory (LSTM) models outperforming traditional climate-only models, offering the potential for more targeted and timely interventions. The value of this research lies in its methodological innovation by incorporating both climate and mobility data into a *machine learning* framework for disease prediction. Unlike traditional epidemiological models, which often rely on static data and limited variables, this study used dynamic, *real-time* data to inform predictions, providing a more nuanced understanding of dengue transmission. By applying *machine learning* techniques such as Random Forest and LSTM, the research contributes to the field of computational epidemiology by demonstrating how these models can improve early warning systems for urban health threats. The approach not only advances *predictive model*ing but also serves as a practical tool for public health officials in resource-constrained environments, helping them optimize resource allocation and response strategies during outbreaks.

Despite the promising results, there are limitations to this study that warrant further exploration. One key limitation is the reliance on historical mobility data, which may not fully capture sudden changes in movement patterns, especially during unanticipated events such as holidays or natural disasters. Additionally, the model's accuracy varied across cities, indicating that local factors such as specific health interventions or cultural behaviors were not fully accounted for. Future research should focus on refining the models by incorporating more granular, *real-time* mobility data and exploring additional environmental variables, such as air quality or vector control measures. Expanding the study to include other Southeast Asian cities with different urban dynamics will also help to generalize the model's applicability. Furthermore, future studies should investigate the integration of socio-economic factors, such as income level or education, to enhance the model's predictive capabilities in diverse demographic settings.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used ChatGPT to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing; Conceptualization; Data curation; In-vestigation.

Author 2: Data curation; Investigation.

Author 3: Formal analysis; Methodology; Writing - original draft; Supervision; Validation.

Author 4: Other contribution; Resources; Visuali-zation; Writing - original draft.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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