



ARTICLE RESEARCH

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Machine Learning Approach to Predict the Dengue Cases Based on Climate Factors

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ABSTRACT

Dengue is a global health issue threatening public health, particularly in developing countries. Effective disease surveillance is critical to anticipate impending outbreaks and implement appropriate control responses. However, delays in dengue case reporting are frequent due to human resource shortfalls. Improved outbreak predictive capacity also requires additional input on vector presence and abundance, which is currently not captured in the surveillance platform. Thus, we developed a prototype AI application, “Dengue Forecasting,” that leverages machine learning methods in filing the dengue case report and incorporates dengue vector and climatic parameters. This application simplifies the recording of dengue cases, vector abundance (*Angka Bebas Jentik*/ABJ/Larvae-Free Index) and selected climatic variables (sun exposure, temperature, humidity, wind speed, and precipitation) in Bandung City. The relevant data were extracted from Indonesia's Ministry of Health and the Meteorological, Climatological, and Geophysical Agency. The entire process, from developing the model to deployment, was conducted under R programming language version 4.2.2 using packages (caret, shiny.io). The linear regression model demonstrated the highest precision (RMSE= 268.32 and MAE= 164.1) in predicting the dengue cases and outbreaks. We also applied this to the application deployment. “Dengue Forecasting” has the potential to assist policymakers at the district level, complementing Dengue EWARS, in anticipating and mitigating dengue outbreaks, especially in Bandung City.

Keywords: Artificial Intelligence, Dengue, Forecasting, Weather, Disease prediction

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INTRODUCTION

Dengue is a global health issue threatening public health, particularly in developing countries. The global burden of dengue fever has increased significantly over the past few decades. If untreated, dengue can trigger an outbreak and cause death. This condition causes a significant burden on society, health systems, and the economy in most tropical countries in the world.⁽¹⁾ According to the World Health Organization (WHO), dengue fever cases reported to WHO increased from 505,430 in 2000 to 5.2 million cases in 2019, with most cases being asymptomatic or mild and therefore not reported. One modeling estimate suggested 390 million dengue virus infections yearly, with 96 million visible infections.⁽²⁾ The disease has been endemic in more than 100 countries, including Indonesia.⁽³⁾ By the end of 2022, Indonesia reported 143.000 dengue cases, with the highest incidence in three provinces, including West Java, East Java and Central Java. More than 50% of the national cases are reported from these regions and 1,236 deaths were reported in 2022.⁽⁴⁾ Bandung City, the capital city of the West Java province, has been affected heavily by dengue. There were 3,743 cases in 2021, which increased to 5,205 cases in 2022. Dengue incidence rate (IR) also elevated from 145 per 100,000 population in 2021 to 201 per 100,000 population in 2022.⁽⁵⁾

Dengue control is very complex and requires multisectoral collaboration and integrated approaches, including coordination and leadership, preparedness and response, case diagnostic, health care facilities, operation support and logistics, case surveillance and management, capacity building, risk communication, community engagement and integrated vector management (IVM).^(3,6) Dengue control programs encountered many challenges. For example, environmental and vector controls require massive infrastructure investment and long-term human behaviour approaches to improve sanitation.^(6,7) Moreover, chemical methods have been used to control *Aedes* larvae and mosquitoes for long periods, but some considerations arise from the method, including accessibility, environmental toxicity, and insecticide resistance. Other ecological controls had been introduced, such as using larvivorous fish to eliminate the mosquito larvae and *Wolbachia pipientis*.⁽⁸⁻¹¹⁾ Although the Indonesian government has put a lot of effort and control measures for the disease, the incidence and fatality rate are still high because of multiple factors such as the absence of active surveillance, insufficient case management, inadequate diagnostic tools, mobilization and urbanization of dengue fever carriers, community density, availability of drugs and vaccines and lack of community participation.⁽¹²⁻¹⁵⁾

Artificial Intelligence (AI), including Machine Learning (ML) and Deep Learning (DL) algorithms, has been introduced in many disciplines, including public health and healthcare settings. The use of AI in public health will help public health practitioners perform any activities automatically, which means it can reduce the workload of health workers, reduce human errors, and improve productivity.⁽¹⁶⁾ One of the advantages of AI is the ability to analyze a large and complex dataset to create models and predictions quickly and efficiently.^(17,18) As explained above, one of the significant issues in dengue control is the lack of surveillance and prediction systems, which leads to delayed responses, preparedness and inappropriate regulation. AI can help to fill this gap for better decision making and disease control. This paper presents a prototype to utilize AI for dengue forecasting in

Bandung City to assist policymakers and public health practitioners in controlling and mitigating the dengue outbreak.

METHODS AND MATERIALS

This study employs machine learning techniques, including Linear Regression, Ridge Regression, Lasso Regression, Regression Tree, Random Forest, and Support Vector Regression, to determine the most accurate model for predicting dengue fever trends from 2018 to 2022.

Lasso and Ridge regression are widely used methods in linear regression to tackle overfitting and enhance the model's generalization ability. They incorporate a regularization component into the conventional linear regression cost function. A regression tree is a kind of decision tree employed in machine learning to handle regression problems. It takes the form of a hierarchy where every internal node makes a decision based on a feature, and each leaf node provides a prediction for the target variable.⁽¹⁸⁾

In contrast, Random Forest is an ensemble learning technique that constructs numerous decision trees during training and produces the average prediction (for regression tasks) of these individual trees. Another ensemble method is the Support Vector Machine (SVM). The SVM is a supervised learning algorithm that aims to find the hyperplane that best separates the data points into different classes while maximizing the margin. Although, this algorithm does not extract the variable of importance.⁽¹⁸⁾

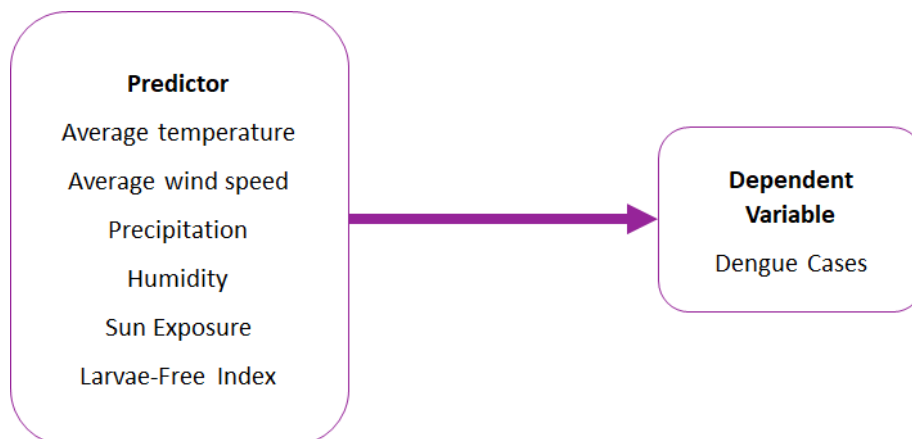


Figure 1. List of predictors and dependent variable

The data utilized consists of climate data from the Meteorology, Climatology, and Geophysics Agency, dengue cases, and vector density (Angka Bebas Jentik/ABJ) from the Ministry of Health. The research design is illustrated in the diagram above (Figure 1).

We divided the data into training and testing sets. The training set forms the basis of the model, while the testing set is used to assess the model's performance. We allocated 80% of the data for training and 20% for testing.

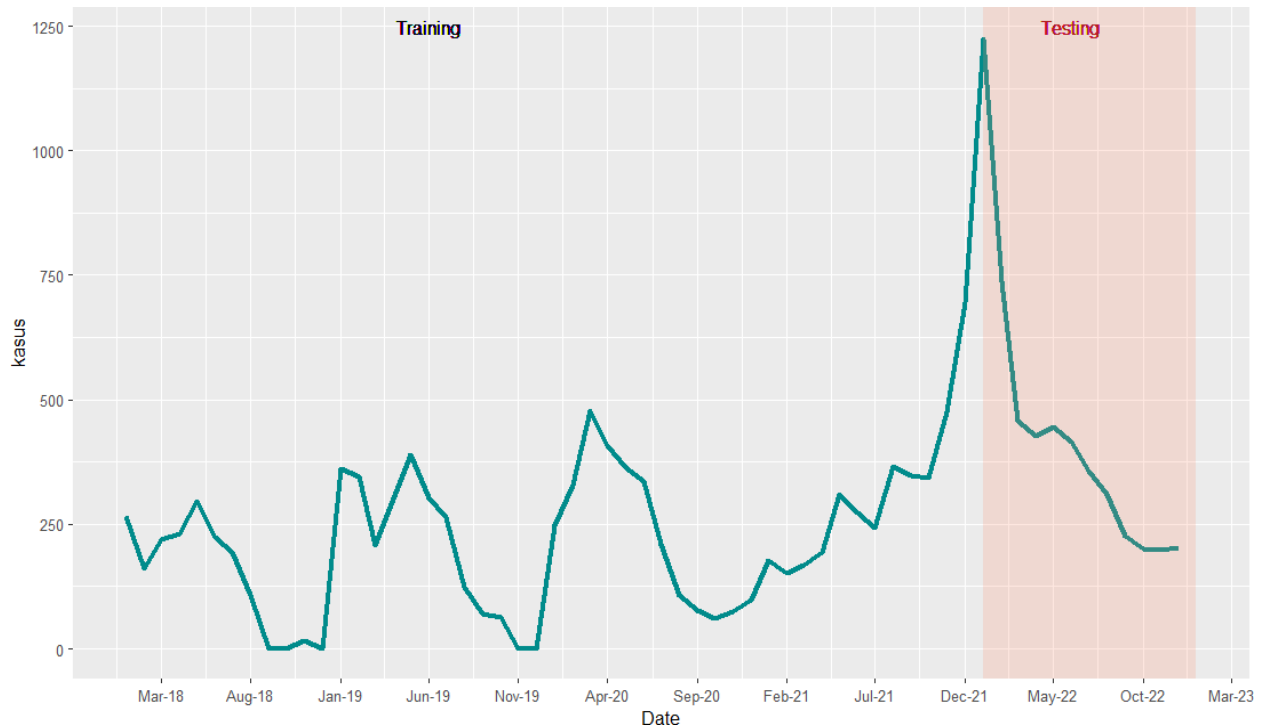


Figure 2. Training and Testing Data Partition

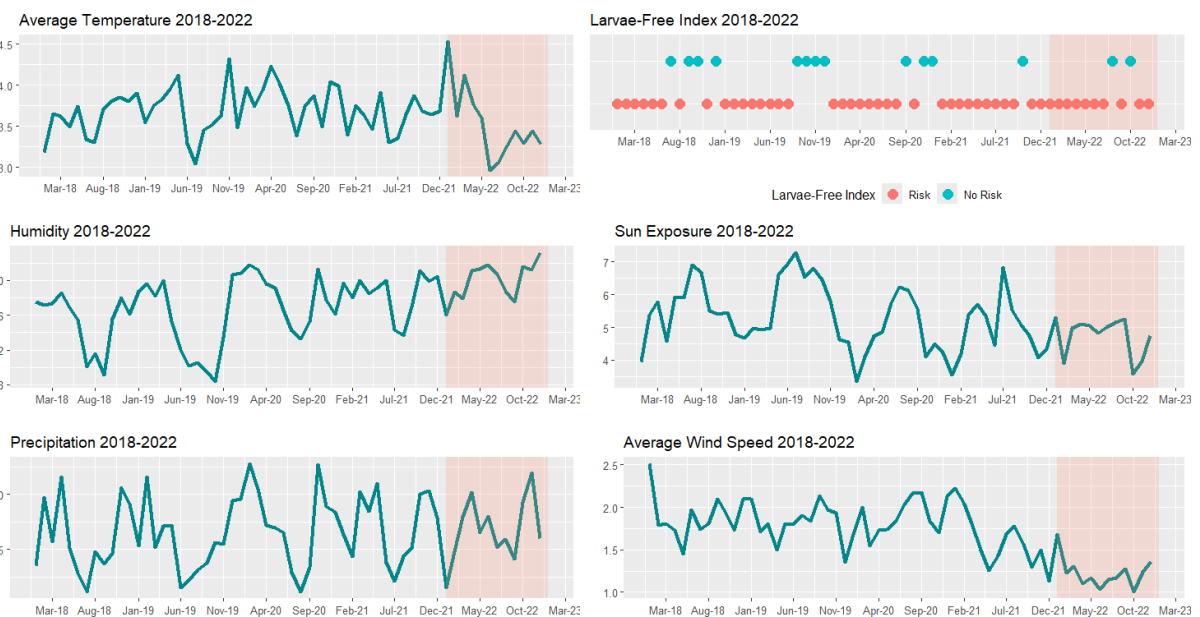


Figure 3. Exploratory Data Analysis of Variables

The training data spanned from 2018 to 2021, while the entire year of 2022 was used for testing. Additionally, we employed a cross-validation method with 5 folds. The machine learning algorithms used in this process were as follows:

Table 1. Algorithm and Hyperparameter values

Algorithm	Hyperparameter values
Linear Regression	
Ridge Regression	alpha = 0 lambda = 61
Lasso Regression	alpha = 1 lambda = 31
Regression Tree	max depths = 5
Random Forest	max depths = 5 ntrees = 120
SVR	epsilon = 0.5

The model's performance will be evaluated using the Root Mean Squared Error (RMSE) for the training test. We were using the testing data where we will assess the RMSE, Mean Absolute Error (MAE), and R^2 . The lowest RMSE and MAE will be selected as the best model.⁽¹⁹⁾

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2}$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |\hat{y}_i - y_i|$$

Formula 1: RMSE and MAE formula

The most effective model will be determined based on these indicators. In this study, we used R version 4.3.0 with a caret package.⁽²⁰⁾

RESULT

Table 2. Model Performances

Models	Mean RMSE	Mean MAE
Linear Regression	268.323	164.106
Ridge Regression	303.948	182.426
Lasso Regression	307.337	181.424
Regression Tree	326.447	206.073
Random Forest	298.039	171.666
SVR	280.195	172.622

The analysis in the table shows that the Linear Regression model is the best model with the lowest RMSE and MAE. We found that the least number of RMSE and MAE was associated with the Linear Regression Model. It means that the model has a better result.

Thorough analysis, the Linear Regression model was determined as the one that performs most effectively in predicting dengue outbreaks, supported by its lower Root Mean Square Error (RMSE) of 268.32 and Mean Absolute Error (MAE) of 164.1. Furthermore, our investigation identifies ABJ and average wind speed as significant influencers on dengue occurrences.

Table 3. Variable of Importance of Models

No	Linear Reg	Ridge Reg	Lasso Reg	Regression Tree	Random Forest	SVM*
1	Larvae-Free Index	Average Wind Speed	Average Wind Speed	Average Wind Speed	Average Wind Speed	N/A
2	Average Wind Speed	Larvae-Free Index	Larvae-Free Index	Average Humidity	Larvae-Free Index	N/A
3	Rainfall Rate	Sun Exposure	Sun Exposure	Larvae-Free Index	Average Humidity	N/A
4	Sun Exposure	Average Temperature	Average Humidity	Sun Exposure	Average Temperature	N/A
5	Average Temperature	Average Humidity	Average Temperature	RR	Sun Exposure	N/A
6	Average Humidity	Rainfall Rate	Rainfall Rate	Average Temperature	Precipitation	N/A

*N/A= Not available

In the table, "Ovitrap" and "Average Wind Speed" emerged as the top two variables of importance across all models.

DISCUSSION

Machine learning algorithms (ML) are gaining significant interest in the creation of predictive models to forecast and monitor dengue transmission rates. Numerous studies have demonstrated the effectiveness of machine learning algorithms to predict the occurrence of cases and outbreaks. Indeed, there exists a wide array of potential machine-learning algorithms for predicting this disease.^(21–23)

This study utilized several machine learning algorithms: Linear Regression, Ridge Regression, Lasso Regression, Support Vector Machine (SVM), Random Forest, and Decision Tree. Those algorithms were based on the previous studies.^(24–27) Those methods also followed K-fold cross-validation (CV) with five folds, which was one of the popular choices for machine learning analysis.⁽²⁷⁾



Figure 4. The Comparisons of Observation (tosca) and Predictions. The ideal model would exhibit the closest pattern to the observed data. Among the models evaluated, including Linear Regression, Ridge Regression, and SVR/SVM, it was found that these models could detect the sharp incline in cases in 2021. Specifically, Linear Regression emerged as the most effective model for dengue prediction.

The results showed that linear regression became the best performance model among every model. These results were different from previous studies in machine learning utilization for dengue cases, where ensemble models became the best preferences for machine learning analysis.^(28,29) This might be caused by the small sample size of this study (only 2018 to 2022), and the model only leveraged a single model to run the prediction compared to the ensemble models.

The climate factors showed an association with dengue cases. Studies showed that precipitation, humidity, rainfall, and temperature possibly affected dengue transmission.⁽³⁰⁾ Temperature became an important factor in the incubation period and the duration of the gonotrophic cycle.^(31,32) On the contrary, this research found that average wind speed emerged as the most significant variable. In machine learning, this indicates the importance of features or variables to the model. Various studies have suggested that monthly wind speed is inversely correlated with dengue incidence. One potential explanation for the impact of wind speed is the reduction in mosquitoes' activity in seeking hosts. This decreased activity can lead to fewer instances of egg-laying and interactions with hosts. Wind may deter mosquitoes from tracking scent trails emitted by hosts, possibly by impeding their ability to fly against the wind or by dispersing the chemical signals produced by hosts.^(33,34)

WHO recommends vector controls as a fundamental approach to preventing disease and

responding to outbreaks of Dengue.⁽³⁵⁾ Indonesia's Ministry of Health translated in using the measurement for vector density, named ABJ (several studies using Larvae-Free Index). These larval and pupal indices remain the most used parameters to measure vector infestation in the community.^(36,37) This method involves visually inspecting various potential breeding sites for *Aedes* mosquitoes. The inspection covers large and small water reservoirs such as drums, buckets, animal water troughs and other containers. If no larvae are initially spotted, a brief observation period of approximately 30 seconds to 1 minute is recommended to ensure thorough examination. For smaller breeding sites like flower vases, potted plants, and bottles with murky water, it may be necessary to relocate the water to facilitate inspection. In cases where inspection is challenging due to darkness or turbidity, a flashlight can be used to aid in the identification of larvae.⁽³⁸⁾ These aggregate data were obtained by dividing the number of houses or buildings where no mosquito larvae were found within a specific time frame by the total number of houses or buildings inspected, then multiplying the result by 100%. An area is deemed larvae-free when the value is equal to or greater than 95%, suggesting a reduced risk of dengue transmission.^(39,40) Those data were recorded in an Indonesia's Ministry of Health Apps named SILANTOR or Surveilans Vektor dan Binatang Kuman Pembawa Penyakit.

The Ovitrap Index became the second variable of importance in every model. These findings are similar to a previous study in Bandung City.⁽⁴¹⁾ On the other hand, this vector measurement is not recognized and recommended by WHO as the monitoring *Ae. aegypti*. Moreover, some previous studies concluded this index does not correlate with the dengue incidence.^(37,42)

This study has several limitations, and the small sample might affect the machine learning performance. SILANTOR is a relatively new application in the Ministry of Health (since 2018), and the report system would rely on volunteers. However, the Ministry of Health or the District Health Office did not consistently monitor the volunteers and the larva survey. This might lead to a problem in data collection and its timely input. Second, there was a delay in the dengue case reporting for approximately several weeks by the Ministry of Health. This will affect the imprecise time series data for modelling. This machine learning could be possible way to solve those gaps.

Moreover, this study does not cover many other potential aspects that might contribute to dengue cases in Bandung City. One of the possibilities is population mobility.⁽⁴³⁾ Since Bandung City became the fourth biggest city in Indonesia, urbanization is inevitable. Studies in Thailand and Brazil suggested the impact of human movement on dengue transmission in local areas.⁽⁴⁴⁻⁴⁶⁾

Follow-up research related to the other machine learning algorithms and hyperparameter tuning is needed to figure out how the model can be tailored to the location where it functions. Besides, there will be a requirement to collect more samples from the district health office to verify the data before it has been used to perform the machine learning model. Thus, it may avoid bias that can be incorporated into the performed model.

CONCLUSION AND RECOMMENDATIONS

In conclusion, this study contributes to the growing body of research on dengue transmission prediction through the application of machine learning algorithms. The findings highlight the effectiveness of linear regression in forecasting dengue cases, underscoring its potential utility in public health surveillance efforts. Notably, climate factors, exceptionally average wind speed, emerged as significant predictors, shedding light on the complex dynamics of dengue transmission. Overall, this study represents a significant step towards developing effective predictive models for dengue transmission, offering valuable insights that can inform evidence-based decision-making and ultimately contribute to the prevention and control of this vector-borne disease.

REFERENCES

1. World Health Organization. Integrating neglected tropical diseases into global health and development: fourth WHO report on neglected tropical diseases [Internet]. Geneva: World Health Organization; 2017 [cited 2024 Mar 6]. 278 p. Available from: <https://iris.who.int/handle/10665/255011>
2. Bhatt S, Gething PW, Brady OJ, Messina JP, Farlow AW, Moyes CL, et al. The global distribution and burden of dengue. *Nature*. 2013 Apr;496(7446):504–7.
3. WHO. Dengue - Global situation [Internet]. World Health Organization; 2023. Available from: <https://www.who.int/emergencies/disease-outbreak-news/item/2023-DON498#:~:text=Weakness%20in%20the%20surveillance%20systems%20in%20many%20affected,transmission%20and%20the%20upsurge%20of%20cases%20and%20deaths.>
4. Kementerian Kesehatan Republik Indonesia. Membuka Lembaran Baru: Laporan Tahunan 2022 Demam Berdarah Dengue [Internet]. Kementerian Kesehatan Republik Indonesia; [cited 2024 Mar 6]. Available from: https://p2p.kemkes.go.id/wp-content/uploads/2023/06/FINAL_6072023_Layout_DBD-1.pdf
5. Dinas Kesehatan Kota Bandung. Profil kesehatan Kota Bandung tahun 2022 [Internet]. Dinas Kesehatan Kota Bandung; 2023 [cited 2024 Mar 6]. Available from: <https://dinkes.bandung.go.id/download/profil-kesehatan-2022/>
6. Deen JL, Harris E, Wills B, Balmaseda A, Hammond SN, Rocha C, et al. The WHO dengue classification and case definitions: time for a reassessment. *The Lancet*. 2006 Jul;368(9530):170–3.
7. Vanlerberghe V, Toledo ME, Rodriguez M, Gomez D, Baly A, Benitez JR, et al. Community involvement in dengue vector control: cluster randomised trial. *BMJ*. 2009 Jun 9;338(jun09 1):b1959–b1959.
8. Lam SK. Challenges in reducing dengue burden; diagnostics, control measures and vaccines. *Expert Review of Vaccines*. 2013 Sep;12(9):995–1010.
9. Turelli M, Hoffmann AA. Rapid spread of an inherited incompatibility factor in California *Drosophila*. *Nature*. 1991 Oct;353(6343):440–2.
10. Hoffmann AA, Montgomery BL, Popovici J, Iturbe-Ormaetxe I, Johnson PH, Muzzi F, et al. Successful establishment of *Wolbachia* in *Aedes* populations to suppress dengue transmission. *Nature*. 2011 Aug;476(7361):454–7.

11. Walker T, Johnson PH, Moreira LA, Iturbe-Ormaetxe I, Frentiu FD, McMeniman CJ, et al. The wMel Wolbachia strain blocks dengue and invades caged *Aedes aegypti* populations. *Nature*. 2011 Aug;476(7361):450–3.
12. FKKMK. FKKMK-UGM. 2016. Demam Berdarah Dengue: Tantangan Indonesia. Available from: <https://fkkmk.ugm.ac.id/demam-berdarah-tantangan-indonesia/>
13. Haryanto B. Indonesia Dengue Fever: Status, Vulnerability, and Challenges. In: J. Rodriguez-Morales A, editor. *Current Topics in Tropical Emerging Diseases and Travel Medicine* [Internet]. IntechOpen; 2018 [cited 2024 Feb 14]. Available from: <https://www.intechopen.com/books/current-topics-in-tropical-emerging-diseases-and-travel-medicine/indonesia-dengue-fever-status-vulnerability-and-challenges>
14. Utama IMS, Lukman N, Sukmawati DD, Alisjahbana B, Alam A, Murniati D, et al. Dengue viral infection in Indonesia: Epidemiology, diagnostic challenges, and mutations from an observational cohort study. Messer WB, editor. *PLoS Negl Trop Dis*. 2019 Oct 21;13(10):e0007785.
15. Tsheten T, Gray DJ, Clements ACA, Wangdi K. Epidemiology and challenges of dengue surveillance in the WHO South-East Asia Region. *Transactions of The Royal Society of Tropical Medicine and Hygiene*. 2021 Jun 2;115(6):583–99.
16. Ghaffar Nia N, Kaplanoglu E, Nasab A. Evaluation of artificial intelligence techniques in disease diagnosis and prediction. *Discov Artif Intell*. 2023 Jan 30;3(1):5.
17. Ramudu K, Mohan VM, Jyothirmai D, Prasad DVSSSV, Agrawal R, Boopathi S. Machine Learning and Artificial Intelligence in Disease Prediction: Applications, Challenges, Limitations, Case Studies, and Future Directions. In: Karthick GS, Karupusamy S, editors. *Advances in Healthcare Information Systems and Administration* [Internet]. IGI Global; 2023 [cited 2024 Feb 14]. p. 297–318. Available from: <https://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/978-1-6684-8913-0.ch013>
18. Habehh H, Gohel S. Machine Learning in Healthcare. *CG*. 2021 Dec 16;22(4):291–300.
19. Chai T, Draxler RR. Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. *Geosci Model Dev*. 2014 Jun 30;7(3):1247– 50.
20. Kuhn M. Building Predictive Models in *R* Using the **caret** Package. *J Stat Soft* [Internet]. 2008 [cited 2024 Mar 7];28(5). Available from: <http://www.jstatsoft.org/v28/i05/>
21. Hoyos W, Aguilar J, Toro M. Dengue models based on machine learning techniques: A systematic literature review. *Artificial Intelligence in Medicine*. 2021 Sep;119:102157.
22. Kakarla SG, Kondeti PK, Vavilala HP, Boddeda GSB, Mopuri R, Kumaraswamy S, et al. Weather integrated multiple machine learning models for prediction of dengue prevalence in India. *Int J Biometeorol*. 2023 Feb;67(2):285–97.
23. Ong SQ, Isawasan P, Ngesom AMM, Shahar H, Lasim AM, Nair G. Predicting dengue transmission rates by comparing different machine learning models with vector indices and meteorological data. *Sci Rep*. 2023 Nov 5;13(1):19129.
24. Guo P, Zhang Q, Chen Y, Xiao J, He J, Zhang Y, et al. An ensemble forecast model of dengue in Guangzhou, China using climate and social media surveillance data. *Science of The Total Environment*. 2019 Jan;647:752–62.
25. Murillo A, B ÁS. Predicting the incidence of dengue in Costa Rica using a decision tree model based on climatic and socioeconomic variables. In: 2021 IEEE V Jornadas Costarricenses de Investigación en Computación e Informática (JoCICI) [Internet]. San José, Costa Rica: IEEE; 2021

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- [cited 2024 Mar 6]. p. 1–5. Available from: <https://ieeexplore.ieee.org/document/9794345/>
26. Tanawi IN, Vito V, Sarwinda D, Tasman H, Hertono GF. Support Vector Regression for Predicting the Number of Dengue Incidents in DKI Jakarta. *Procedia Computer Science*. 2021;179:747–53.
 27. Zhao N, Charland K, Carabali M, Nsoesie EO, Maheu-Giroux M, Rees E, et al. Machine learning and dengue forecasting: Comparing random forests and artificial neural networks for predicting dengue burden at national and sub-national scales in Colombia. Choisy M, editor. *PLoS Negl Trop Dis*. 2020 Sep 24;14(9):e0008056.
 28. Fang L, Hu W, Pan G. Meteorological factors cannot be ignored in machine learning-based methods for predicting dengue, a systematic review. *Int J Biometeorol*. 2024 Mar;68(3):401–10.
 29. Leung XY, Islam RM, Adhami M, Ilic D, McDonald L, Palawaththa S, et al. A systematic review of dengue outbreak prediction models: Current scenario and future directions. Poonawala H, editor. *PLoS Negl Trop Dis*. 2023 Feb 13;17(2):e0010631.
 30. Abdullah NAMH, Dom NC, Salleh SA, Salim H, Precha N. The association between dengue case and climate: A systematic review and meta-analysis. *One Health*. 2022 Dec;15:100452.
 31. Brady OJ, Johansson MA, Guerra CA, Bhatt S, Golding N, Pigott DM, et al. Modelling adult *Aedes aegypti* and *Aedes albopictus* survival at different temperatures in laboratory and field settings. *Parasites Vectors*. 2013 Dec;6(1):351.
 32. Messina JP, Brady OJ, Golding N, Kraemer MUG, Wint GRW, Ray SE, et al. The current and future global distribution and population at risk of dengue. *Nat Microbiol*. 2019 Jun 10;4(9):1508–
 33. Cheong Y, Burkart K, Leitão P, Lakes T. Assessing Weather Effects on Dengue Disease in Malaysia. *IJERPH*. 2013 Nov 26;10(12):6319–34.
 34. Gui H, Gwee S, Koh J, Pang J. Weather Factors Associated with Reduced Risk of Dengue Transmission in an Urbanized Tropical City. *IJERPH*. 2021 Dec 29;19(1):339.
 35. WHO. Global Vector Control response 2017-2030. World Health Organization; 2017.
 36. Chang FS, Tseng YT, Hsu PS, Chen CD, Lian IB, Chao DY. Re-assess Vector Indices Threshold as an Early Warning Tool for Predicting Dengue Epidemic in a Dengue Non-endemic Country. Scarpino SV, editor. *PLoS Negl Trop Dis*. 2015 Sep 14;9(9):e0004043.
 37. Garjito TA, Hidajat MC, Kinansi RR, Setyaningsih R, Anggraeni YM, Mujiyanto, et al. Stegomyia Indices and Risk of Dengue Transmission: A Lack of Correlation. *Front Public Health*. 2020 Jul 24;8:328.
 38. Suryanegara FDA, Suparmi S, Setyaningrum N. The Description of Larva Free Index as COMBI (Communication for Behavioral Impact) Dengue Hemorrhagic Fever Prevention Indicator. *Kemas*. 2018 Apr 2;13(3):338–44.
 39. Nurmayanti D, Mukarromah HN, Marlik M, La Ane R. Geographic Distribution of DHF Cases and Larvae Free Index In Situbondo Regency, 2019-2021. *MKMI*. 2023 Mar 31;19(1):9–18.
 40. Sukei TW, Astuti CT. HUBUNGAN ANGKA BEBAS JENTIK (ABJ) DENGAN INSIDENCE RATE DEMAM BERDARAH DENGUE (DBD) DI TINGKAT KABUPATEN SLEMAN TAHUN 2013-2017. *Jurnal Kesehatan dan Pengelolaan Lingkungan*. 2020 Jul 1;1(2):57–63.
 41. Sasmita HI, Neoh KB, Yusmalinar S, Anggraeni T, Chang NT, Bong LJ, et al. Ovitrap surveillance of dengue vector mosquitoes in Bandung City, West Java Province, Indonesia. Ramos AN, editor. *PLoS Negl Trop Dis*. 2021 Oct 28;15(10):e0009896.
 42. WHO. Control of Neglected Tropical Diseases. n.d.
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43. Sari SYI, Adelwin Y, Rinawan FR. Land Use Changes and Cluster Identification of Dengue Hemorrhagic Fever Cases in Bandung, Indonesia. *TropicalMed*. 2020 May 2;5(2):70.
 44. Churakov M, Villabona-Arenas CJ, Kraemer MUG, Salje H, Cauchemez S. Spatio-temporal dynamics of dengue in Brazil: Seasonal travelling waves and determinants of regional synchrony. Althouse B, editor. *PLoS Negl Trop Dis*. 2019 Apr 22;13(4):e0007012.
 45. Faridah L, Mindra IGN, Putra RE, Fauziah N, Agustian D, Natalia YA, et al. Spatial and temporal analysis of hospitalized dengue patients in Bandung: demographics and risk. *Trop Med Health*. 2021 Dec;49(1):44.
 46. Phanitchat T, Zhao B, Haque U, Pientong C, Ekalaksananan T, Aromseree S, et al. Spatial and temporal patterns of dengue incidence in northeastern Thailand 2006–2016. *BMC Infect Dis*. 2019 Dec;19(1):743.