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MACHINE LEARNING APPROACHES FOR DENGUE PREDICTION: A REVIEW OF ALGORITHMS AND APPLICATIONS

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ABSTRACT

Dengue disease positions a significant global public health challenge, warranting attention from local health authorities and the international community. The escalating number of reported cases necessitates early detection to mitigate the risk of disease transmission. This review paper examines the application of various machine learning (ML) algorithms in predicting the spread of Dengue within communities. Our investigation encompasses a range of ML techniques, including Self-Organizing Maps, Decision Trees, Support Vector Machines, neural networks, fuzzy systems, and evolutionary algorithms and classifiers. Leveraging ML computation, these techniques demonstrate high levels of predictive accuracy, offering valuable insights for dengue prediction. Effective control measures and timely assessment of cases using ML can significantly reduce dengue risk. To implement the proposed policy, geographic variables and local statistical data should be incorporated within the ML framework. Collaboration between health scientists and data scientists in employing ML approaches can lead to the development of innovative methods for diagnosis, treatment, emergency management, and prediction of Dengue. Ultimately, these techniques may inform policy development and contribute to disease eradication efforts.

KEYWORDS: Dengue, Risk assessment Model, Machine learning, Prediction, Artificial intelligence, Health policy

INTRODUCTION

Dengue disease continues to position a significant global public health concern, with a rising number of reported cases worldwide (Eisen & Eisen, 2011). As a substantial challenge for local health authorities and the international public health community, effective strategies for detecting and predicting dengue spread are essential to mitigate its impact. In recent years, machine learning (ML) algorithms have emerged as valuable tools for analysing complex datasets and predicting disease patterns. By harnessing the power of ML, researchers have explored various techniques to improve dengue prediction and enhance public health interventions (Gambhir et al., 2018).

This review paper aims to provide a comprehensive overview of the application of ML algorithms in predicting the spread of Dengue within communities. ML techniques, ranging from Self-Organizing Maps to Support Vector Machines, Decision Trees, neural networks, fuzzy systems, evolutionary algorithms, and classifiers, have demonstrated promising results in forecasting dengue outbreaks. Furthermore, by analysing diverse datasets and incorporating geographical variables and local statistical data, ML approaches offer valuable insights for understanding dengue transmission dynamics and designing effective prevention and control measures.

The early detection of dengue cases plays a crucial role in curbing the spread of the disease. ML algorithms enable the rapid assessment of growing dengue cases, providing timely information for public health authorities to implement targeted interventions (Saturi, 2020). By combining the expertise of health scientists and data scientists, innovative ML-based techniques can be developed to improve diagnosis, treatment, emergency management, and prediction of Dengue. In addition, these approaches have the potential to enhance the accuracy and efficiency of dengue risk assessment, allowing for more informed decision-making and resource allocation.

Furthermore, this review highlights the significance of collaboration between researchers, policymakers, and healthcare professionals in utilising ML techniques for policy development and disease eradication efforts. By leveraging the power of ML and incorporating local contextual factors, a comprehensive understanding of dengue dynamics can be achieved, paving the way for tailored strategies to combat this global health threat. In the succeeding sections of this review paper, we have converse delve into the specific ML algorithms utilised for dengue prediction, discussing their strengths, limitations, and potential applications. Additionally, we have explored the importance of integrating geographical variables, statistical data, and domain expertise into ML models to enhance their accuracy and relevance. Finally, we have discussed the implications of ML-based approaches for public health, emphasising the role of data-driven decision-making and the potential for widespread adoption of preventive measures and targeted interventions.

This review aims to provide a comprehensive and critical analysis of the current state of ML-based approaches for dengue prediction, shedding light on their effectiveness, limitations, and future directions. Furthermore, by synthesising existing knowledge and identifying gaps in the literature, we hope to contribute to the ongoing efforts to combat Dengue and improve public health outcomes.

MATERIAL AND MEATHODS

We utilised two ways to look for and evaluate various studies and literature on Machine Learning models and their applications for Dengue. The first was finding works on Machine Learning Models for assessment and prediction. The other methods are by using science direct. We used the digital library of a comprehensive article database www.sciencedirect.com (Support ScienceDirect, 2022). We identify and classify the studies with machine learning, the search based on keywords such as dengue diagnosis, epidemiology, treatment, and prediction with associated factors such as climate, land use, socioeconomic, Spatio-temporal, and Time series with inclusion criteria.

The inclusion criteria contain literature through Key words, only English language papers and within recent times (mainly last ten years), the keywords used as table1. The other technique, which uses the dengue and modelling approach with ML, is based on a random search (ScienceDirect, Google Scholar, IEEE, Scopus and PubMed), the papers purely includes ML models, algorithms, and methodologies with Dengue, outcomes of the search displayed in Table 2.

RESULTS AND DISCUSSION

Vector-Borne Disease is caused by an infection spread by blood-feeding arthropods such as mosquitoes, ticks, and fleas to people and other animals (Kaur et al., 2021). Dengue fever, West Nile Virus, Lyme disease, and malaria are examples of vector-borne illnesses (Patz et al., 1998). Dengue is a vector-borne viral disease transmitted by the domestic mosquito Aedes aegypti. These diseases are commonly connected with poverty and inequality. Several are chronic, debilitating, and stigmatising, making matters worse. Over the last three decades, specific formerly controlled ailments have spread and gradually plagued disease-free areas while remerging in areas where they had faded for decades. Still, vaccines and treatments for some of these illnesses are few and sometimes ineffective. Insecticide resistance is also on the rise, which also makes it difficult.

Globally infectious diseases are rising, and it has a significant share. Almost 50% of infections are vector-borne pathogens (WHO, 2010). The situation worsens in developing countries with rising morbidity and mortality due to vector-borne diseases (Eisen & Eisen, 2011, Parselia et al., 2019). The rising vector-borne disease (VBD), like dengue fever, is hazardous to susceptible people, especially in hot, tropical and semi-tropical regions. Due to rapid population growth and the abundance of breeding grounds, metropolitan cities and their surroundings are more vulnerable (Delmelle et al., 2014).

Mosquitoes are major vectors for the spread of a pathogen transmitted by an arthropod vector. Various strategies are used to measure mosquito abundance over time, identify the leading causes of mosquito population patterns, and assess mosquito management options (Cailly et al., 2012; Delmelle et al., 2014). The risk of Dengue affects over 40% of the world's population. A predictable 2.5 billion individuals are at hazard from dengue contamination, and collectively dengue infections are one of the foremost imperative mosquito-borne infections spread to people. Uncleanness and pollution in metropolitan cities flourishes Dengue's primary mosquito vector Aedes aegypti that is responsible for up to 70-80% of populations (Patz et al., 1998; Chiodini & Boyne, 2014).

Physical factors such as temperature is a crucial climatic variable contributing to the occurrence of dengue fever (Stolerman et al., 2019). For example, in an environmental-controlled experiment, the temperature was the most conducive to mosquito larvae, pupae, and eggs surviving. Other factors such as rainfall, humidity, vegetation, precipitation, wind speed, wind direction, human population, animal population, pathogens (e.g., protozoa), and the mosquito life cycle, socioeconomic and demographic variables are responsible, and these are analysed in many domains including artificial intelligence to identify the affecting rates of dengue fever (Uusitalo et al., 2019).

Many research studies have found that hazard mapping studies are primarily descriptive, with minimal validation and predictive value (Wen et al., 2006; Hsueh et al., 2012). As a result, new techniques for dengue prediction, such as assessing climate and movement data, are necessary. Climatic and climatic data were extensively used in producing prediction risk maps and dengue incidence modelling. Researchers observed that inter-annual and seasonal climate fluctuations influenced dengue virus transmission significantly. The geographical information system also mapped the dengue threat and risk's spatial distribution and vulnerability (Gubler, 1998, Stolerman et al., 2019). One of the most important health initiatives for reducing mortality and the severity of dengue epidemics in many countries is early detection. Dengue management, including surveillance, monitoring, and early warning systems, is required in possible hotspot locations. Machine learning (ML) is used to analyse health and provide early warnings (Caicedo-Torres et al., 2016; Alqaissi et al., 2022). Machine learning (ML) is involved with computers function and methods with ease in programming. Artificial intelligence's machine learning field is used to uncover hidden knowledge without complications. Classification, relapse, positioning, grouping, and measurement are the main categories in ML methods (Wang et al., 2016).

3.1. Machine Learning Models for assessment and prediction

There are several machine-learning techniques, including supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. These can be classified by data type and methods for results. For example, the ML algorithms could evaluate the patient's symptoms to determine how probable it is that the user would develop the disease and its prediction (Beam & Kohane, 2018; Zhou, 2018).

Investigating the prediction using ML and Computation Intelligence supports prediction with models and algorithms. It is used to forecast the probability of an unclear result. Excellent forecasting techniques are provided for fortification. These prediction techniques are decision trees, random forests, enhanced decision trees, Monte Carlo simulations, and relapse (Salim et al., 2021). A growing area of research called geo-computation promotes using computationally rigorous techniques for geographical data analysis, including neural networks, search algorithms, and cellular automata. Since more health-related data is being gathered within a topographical frame of reference, geo-computational methodologies have increased the potential for analysing well-being data (Janssen et al., 2019).

Predictive modelling is a procedure that analyses patterns in input data collection to predict future events or outcomes. These models are used to estimate the long-term result based on many variables (Mishra et al., 2019; Medina-Ortiz et al., 2020; Baker et al., 2022; Kaur et al., 2022; Alqaissi et al., 2022). A type of instructional design known as directed learning is used for inputs with uncertain end requirements. Using these labelled examples, the calculation is conducted in supervised learning. There are many ML methods, such as diverse models, Multiple Linear Regression (MLR), Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), Decision Tree (DT), Nearest Neighbour (NN), Gaussian Naive Bayes (GNB), Bayesian Network (BN) are applied to build a model.

Unsupervised learning organises without labels. It is up to the model to spot patterns in incoming datasets and categorise them using specified rules or correlations. Unsupervised learning can be broken down into different tasks, such as clustering, for which Principal Component Analysis (PCA), Independent Component Analysis (ICA), and k-Means (KM) are used to create models (Natali et al., 2021). The process algorithm picks up how to execute the action from earlier knowledge. Prediction modelling makes use of several well-known methods, such as Nearest Neighbour, Naive Bayes, Decision Trees, Linear Regression, Support Vector Machines (SVM), and Neural Networks are being used in several recent studies.

For the monitoring, control, and prevention of VBD, such as mosquito-borne Dengue and West Nile virus, advances in artificial intelligence, spatial innovation, and decision support frameworks are on the rise (Eisen & Eisen., 2011; Dharmawardana et al., 2017). For example, Rachata et al. (2008) suggested a programmed prediction framework for Dengue Hemorrhagic Fever (DHF) episode risk using an entropy technique and a synthetic neural network. The ANN is modelled after the human brain, which comprises neurons. An artificial neural network is built using layers for input, release, and security. A layer's mobility and weight are intertwined. The neural network's weights' error rate is calculated by comparing the input to another layer and reinforcing the input to the input layer. Helped by an artificial neural network and the entropy approach, this platform offered a programmed chance evaluation demonstration of Dengue. External factors included air temperature, precipitation, and associated meteorological variables.

Fuzzy logic is also a division effectively associated with many areas (Rachata et al., 2008; Zarandi et al., 2011; Torres et al., 2014), such as design response, therapeutic application, and processer revelation. Many scientists (Nakandala & Lau., 2012; Kasbe & Pippal, 2019) have defined the ability to manage ambiguity and unstructured decision-making. Torres et al. describe a methodological strategy that blends multi-resolution investigation and fuzzy frameworks to address dengue cases and severe Dengue in Colombia. This is carried out and compared with a split of findings. This has been applied with success to a variety of fields. Analysts in the medical industry frequently use it due to its capacity to deal with uncertainty (Swe & Tun, 2020).

The genetic algorithm, sometimes known as GA, was developed by John Holland at the College of Michigan in 1975 and is the most well-known Developmental Calculation. The computation entails these steps: a) coding the problem; b) developing an introduction populace; c) determining well-being; d) hybridisation (breeding); and e) change. A robust method for problem-solving optimisation is a genetic algorithm. Genetic computation is based on genetic principles in constructing the lifespan and a technique for revealing precise or appraised outcomes to upgrade or seek issues. Sharp abilities are helpful in many fields today, including assessing the likelihood of diseases. Khanlarpour et al., 2013 used fuzzy reasoning as a decision-making tool in the therapeutic sector (Saturi, 2020).

A decision tree, a supervised machine learning technique, may solve classification and regression problems. A decision tree is a set of options to arrive at an outcome. Random Forest is a machine-learning approach that uses many decision trees to form conclusions. Random Forest uses the ensemble-learning system. The cluster of classifiers can decide by randomly categorising the tree based on attributes at each hub. It is used in dengue research and health-related studies (Ong et al., 2018)

Support vector machines (SVM) is a classification technique that uses a directed learning tool. The SVM was initially introduced, and because of its propensity to have greater observational performance, it received much consideration from specialists (Caicedo-Torres et al., 2016). The SVM may be a prediction tool that uses machine learning theory to increase predictive accuracy while unavoidably avoiding overfitting the data. The ideal hyperplane computation, the part capacities, and the learning hypothesis are three of the SVM's main components (Gambhir et al., 2018).

Self-Organizing Map (SOM) is a form of Artificial Network influenced by biological models of neural systems developed in the 1970s. It works in unsupervised learning and trains its network using a competitive learning algorithm. The result, known as a map, is a discretised representation of the input space (Macedo et al., 2019). The rapid spread of vector-borne dengue fever diseases poses a risk to tropical populations. Quick space-time analyses are needed for this hazard assessment, correct epidemic identification, and mitigation strategies. A deeper understanding of the range of biological and physical factors is necessary to predict how a changing environment may affect dengue diseases (Fathima & Hundewale, 2012). In addition, the model may vary with time and space as local to regional settings transform from time to time.

3.2. Literature research on Machine Learning and Dengue

To pick acceptable literature research subjects within the context of the dengue search. A detailed review of various studies has covered many themes of dengue diagnosis, management, prediction, policy, and modelling. Most risk assessment studies have been observational, with limited validation and predictive utility. As a result, new approaches, such as evaluating climate and movement data in dengue prediction, are essential. Climatic and environmental data are frequently employed in developing prediction risk maps and modelling dengue prevalence. Several research studies have been explored to assess dengue and health issues with ML by different research portals (Table 1). We find numbers of articles with inclusion criteria contain literature through Keyword searching, and important papers appeared (Table 1).

Table1: Search strings used with inclusion criteria in searching, Reference work and Domain

Searching words	Reference work	Topic/Domain

machine learning AND Dengue AND diagnosis	Hoyos et al., 2022	Clinical Management
	Han et al., 2021	Screening Of Infected Patients
machine learning AND Dengue AND warnings	Ismail et al., 2022	Early Warning System
	Adhikari et al., 2020	Early Warning System
machine learning AND Dengue AND prediction	Chakraborty et al., 2019	Forecasting Dengue
	Anggraeni et al., 2017	Predicting the Number of Dengue
	Guo et al., 2019	Forecast Mode
machine learning AND Dengue AND climate	Wieland et al., 2021	Climate And Regional Mosquito Habitat Model
	Souza et al., 2022	Dengue Outbreaks Climate Data
machine learning AND dengue AND time series	Francisco et al., 2022	Disease Dynamics
	Jácome et al., 2019	Modelling For Climate
machine learning AND Dengue AND location	Fischer et al., 2011	Climatic Suitability
	Uusitalo et al., 2019	Environmental And Anthropogenic Factors
	Machado-Machado et al., 2012	Empirical Mapping
machine learning AND Dengue AND treatment	Santos et al., 2019	Detecting Disease Vectors
	Xu et al., 2020	Peak Of Dengue
machine learning AND Dengue AND outbreak	Li et al., 2021	Extreme Outbreak
	Zhang et al., 2022	Outbreak

machine learning AND dengue AND land use	Cheong et al., 2014	Land Use Factors
	Vaddiraju et al., 2022	Urbanisation
machine learning AND Dengue AND epidemiology	Singh et al., 2021	Epidemiology
	Rustam et al., 2022	Models For Disease Epidemiology
machine learning AND Dengue AND Spatio-temporal	Yip et al., 2022	Spatio-Temporal Detection
	Passos et al., 2022	Spatio-Temporal Consistency
machine learning AND Dengue AND socioeconomic	Mutheneni et al., 2018	Cluster Analysis of Dengue
	Chen et al., 2020	Socioeconomic Factors on Dengue
machine learning AND Dengue AND policy	Khurshid et al., 2019	Policy Innovation
	Schwalbe et al., 2020	Global Health
machine learning AND Dengue AND management	Cunha et al., 2021	Management
	Ikerionwu et al., 2022	Vector Management
machine learning AND Dengue AND environment	Cunha et al., 2021, Gangula et al., 2023,	Dengue and Environment
machine learning AND Dengue AND spatial	Rahman et al., 2021	Spatial Distribution
machine learning AND Dengue AND mapping	Berrang-Ford et al., 2021	Global Research
machine learning AND Dengue AND modelling	Scavuzzo et al., 2018	Remote Sensing Data and Modelling
	Lim et al., 2020	Modelling The Epidemic

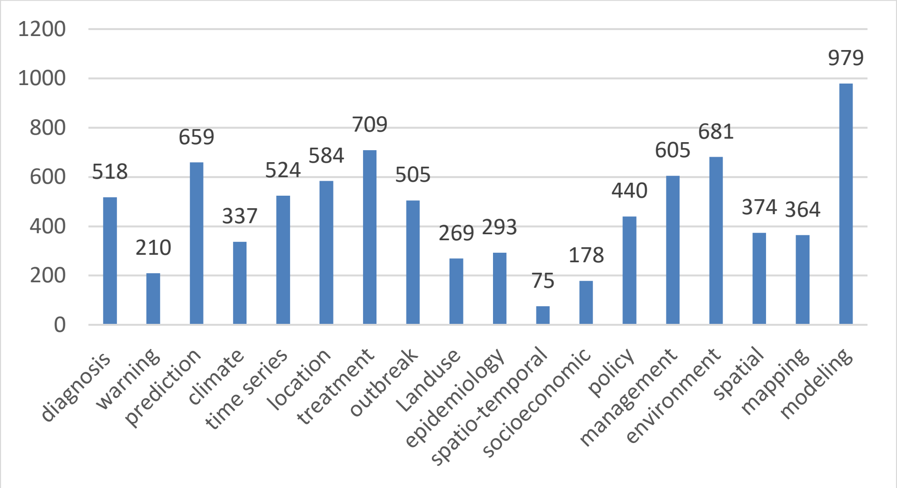

Fig 1: Numbers of papers appear with each keyword.

In searching papers, several papers emerge with each key term (figure1). For each keyword search, the most publications occurred for diagnosis (518), prediction (659), treatment (709), outbreak (505), management (605), environment (681), and most inside modelling (979).

Most publications are in the modelling technique with ML and dengue investigations. The other approach, which employs Dengue and a modelling approach using ML, is based on a random search of ML models, algorithms, and methods for Dengue, the results of which are shown in Table 2.

Table 2: A list of selected machine learning techniques used for dengue modelling, management and prediction

Techniques/ Methodologies	Feature(s) /Dataset Used	Gap/Prospective Work	Reference
Unsupervised machine learning techniques a. Self-organising maps (SOM) b. Random forest algorithms	Clinical Variable: a. Patient data Demographic data Population data	longitudinal approach and models	Macedo et al., 2019

Fuzzy Modelling techniques	Climate Dataset: a. Long-term Average Climate Data Monthly mean temperature, precipitation b. Cloud Cover c. Development Rates d. Survival Rates	fuzzy systems a. Multi-resolution analysis and fuzzy model identification (MRA + FMID) b. Gustafson–Kessel (GK) algorithm c. Takagi–Sugeno model	Torres et al., 2014.
Mapping dengue risk	Diseases Data a. Dengue Cases a. Entomological data b. Breeding percentage in the earlier year c. Demographic Data i)Population Density d. Environmental Data i. Vegetation Index ii. Connectivity iii. index e. The portion covered by residential areas	Random Forest a. Statistical analysis b. Ensemble machine learning method	Ong et al., 2018
Unsupervised Machine Learning Techniques	Diseases Data a. Dengue Cases Demographic Data a. Population Density b. Education coverage Environmental Data a. Rainfall b. Vegetation c. Temperature	Random forest is an unsupervised tree based. a. Random forests b. Artificial Neural Networks c. ARIMA models.	Zhao et al., 2020

	Gini Index		
Supervised learning technique for classification	Diseases Data a. Epidemiological Dengue Cases Demographic Data a. Population Density b. Education coverage Environmental Data a. Rainfall b. Temperature	Machine learning and climate-based early warning systems a. SVM algorithm b. SVM kernel c. SVM threshold Prediction strategy a. Earliest as Possible (EP) b. Average of All (AA	Stolerman et al., 2019
Supervised learning technique for classification a. ANNs b. Support Vector Machine (SVM) c. J48 d. SVM e. Decision trees f. K-Nearest Neighbour (KNN)	Demographic Data a. Population Density Environmental Data b. Rainfall c. Temperature Socioeconomic conditions a. Running water b. Hygiene Services c. Electric Lighting d. Socioeconomic Status Index (SES)	High-Performance Computing with artificial intelligence and ensemble modelling	Parselia et al., 2019

Supervised learning technique for classification a. SVM algorithm b. Decision Trees (CART) c. Artificial Neural Network (MLP) d. SVM (Linear, Polynomial, RBF) e. Bayes Network (TAN) Statistical Modelling Techniques a. Poisson Regression b. Negative Binomial Regression c. Autoregressive Integrated Moving Average (ARIMA) d. Generalised Additive Modelling (GAM).	Environmental Data a. Temperature b. Wind speed c. Humidity d. Rainfall	Deng Zhao ue outbreaks by a. CART, a. ANN, b. SVM and c. Naïve Bayes model	Salim et al., 2021

Machine learning (ML) and artificial intelligence advancements have enormous potential advantages for patients. Predictive analytics powered by machine learning is widely employed in hospital operations and service delivery. Health Scientists must understand how ML may be used in health and policy. We learn many things from this review, and scientist can further use the ML approaches according to available data and need. The future of health care with ML is obvious. Vector-borne diseases such as Dengue can be predicted, managed, and controlled with the help of developed machine learning models (Francisco et al, 2021).

3.3. Future Issues and policy development

Dengue and other vector-borne diseases can be predicted using a modelling approach. The outcome of modelled results can help formulate policies at local and national levels, especially for disease control programs. Several forecasting algorithms have been developed to predict Dengue. These models are based on a prior understanding of the relationship between evident biological and environmental factors. If these relationships are applied to real-time, periodic or seasonal datasets in a spatiotemporal context, the decision maker can be informed in advance with when and where information. It is therefore suggested that the technology solutions should be used not only as a part of the vector-borne disease-related research but also for their management, control, and eradication. The field is still open for new development, and more studies are needed to produce better machine-learning algorithms that can predict Dengue with greater accuracy in regional settings.

The development, integration, and fusion of diverse ML and spatial modelling approaches could be prioritised to create high-quality and precise data for prediction and decision support systems. In order to build a better decision support system with ML algorithms, centralised vector-borne epidemiologic data should be developed. It is to construct reliable models and risk maps for achieving and controlling pathogen and exposure sites for Dengue. Also, a list of potential individual factors, such as understanding the biological variations between healthy and pathological states, requires understanding gene expression data. Finally, it is also important to evaluate the local environmental factors to assess dengue illness prognoses. With a better decision support system for forecasting dengue epidemics, policymakers can apply the strategy and select the best machine learning method after evaluating various approaches.

CONCLUSION

In conclusion, this review paper explores the application of various machine learning (ML) algorithms in predicting the spread of Dengue within communities. The escalating number of Dengue cases worldwide necessitates early detection to mitigate the risk of disease transmission. The study examines a range of ML techniques, including Self-Organizing Maps, Decision Trees, Support Vector Machines, neural networks, fuzzy systems, and evolutionary algorithms and classifiers, which have shown high levels of predictive accuracy in dengue prediction. The findings suggest that effective control measures and timely assessment of cases using ML can significantly reduce the risk of Dengue. To implement the proposed ML models, it is recommended to incorporate geographic variables and local statistical data within the framework. Collaboration between health scientists and data scientists in employing ML approaches can lead to the development of innovative methods for diagnosis, treatment, emergency management, and prediction of Dengue. The review also highlights the importance of considering various factors such as temperature, rainfall, humidity, vegetation, population demographics, and mosquito life cycle in dengue prediction models. Additionally, it emphasises the need for improved risk assessment and early warning systems in potential hotspot locations. Overall, the application of machine learning techniques in dengue prediction holds promise for informing policy development and contributing to disease eradication efforts. Continued research and collaboration in this field can lead to advancements in the monitoring, controlling, and preventing vector-borne diseases like Dengue, ultimately improving public health outcomes worldwide.

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