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Intelligent Systems for Efficiently Predicting and Managing Dengue Fever using Machine Learning Techniques

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Abstract

Dengue fever's high frequency and the possibility of catastrophic outbreaks render major worldwide health concerns in tropical and subtropical areas. Existing model for dengue fever prediction and treatment based on their static models and epidemiological surveillance, often fails to capture the intricate interactions among biological, social, and environmental elements. This study examines, recent developments in machine learning (ML) algorithms for precisely predicting and controlling dengue outbreaks. The review process concentrates on several ML models for forecasting dengue risk and incidence. The forecast accuracy is enhanced to integrate a variety of statistics, such as vector indices, population density, and meteorological variables. The deep learning model utilizes geographical and temporal data to surpass existing models. The review process highlights the results of the ML method for predicting outbreaks identifying high-risk areas, and allocating resources for intervention strategies. The findings of the hybrid ML architectures and real-time data attain greater reliability and accuracy. To enhance model robustness and report points out the gaps in previous research, including the requirement for uniform datasets and socioeconomic elements. This paper paves the way for generating intelligent systems for the proactive management of dengue fever by providing the vital role that ML plays in minimizing the disease's negative effects on public health.

Keywords: Machine Learning, Dengue Fever, Intelligent Systems, Outbreak Management, Data-Driven Epidemiology, Public Health Optimization.

I. INTRODUCTION

Globally, Dengue most quickly spreads over vector-borne viral sicknesses, with expanding territories in danger. Many researchers worked on various measures to control and prevent the spread of disease (Saturi, S., 2020). It infects 390 million people annually in 128 countries. Forecasting mechanisms assist in proactive planning and response for clinical and public health services. Human and financial costs of dengue are alleviated through intervention strategies, health care services, and supply chain management, with timely warnings through forecasting models. The majority of existing dengue forecasting models as time series methods and typically Autoregressive Integrated Moving Average (ARIMA), lagged meteorological factors that covariate with the historical dengue data for oneto 12 weeks ahead forecasting (Zhao et al.,2020).The review paper aims to offer a detailed analysis of ML algorithms utilization in forecasting dengue outbreaks in local communities. This study highlights the value of cooperation among researchers, legislators, and medical practitioners using ML models to create policies against disease. By leveraging the power of ML and incorporating local contextual factors, a comprehensive understanding of dengue dynamics is achieved and paves the way for strategies to combat global health threats. The recently published works has advantages and disadvantages by utilizing the ML models for dengue prediction.

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The accuracy and applicability of ML model investigates by employing the significance of statistical data, domain knowledge, and spatial variables.In summary, the ML model has significant impacts on public health that reflects the need of data-driven decision-making system, treatment and preventative actions. The detailed review of several ML model forthe dengue prediction, offers acritical and comprehensive analysis for future advancement.

II. MATERIAL AND METHODS

Theseveral machine learning (ML) models are employed for a dengue prediction. The different ML models are employed for performing the dengue diagnosis of epidemiology, treatment, and prediction based on the climate data, land usage, socioeconomic status, spatiotemporal, and time series data. The ML method's advantages and the Dengue outcomes are included in the studies.

A. Machine Learning Models for Assessment and Prediction

Several ML methods exist such as reinforcement learning, supervised learning, unsupervised learning, and semi-supervised learning. These methods are utilized based on thedata type and results-oriented and classification purpose. For instance, these models can evaluate the likelihood of a user with a condition that should assess the patient's symptoms.

To anticipate dengue outbreaks by using the machine learning-based methodincorporates essential meteorological parameters such as the TempeRain factor (TRF) introduced by Yavari Nejad, et al., 2021. The most significant climate variablesfed into severalmachine learning models after performing the correlation analysis process.Five classification modelsBayes Network and Support Vector Machinewere tested and evaluated using four years' worth of data from Malaysia, this model achieves an accuracy rate of 92.35%, the TRF's integration process improves the prediction accuracy of dengue outbreaks and it seeks to encourage to the public health management and enhancing the efficacy of dengue epidemic prediction systems. Salim et al., 2021 offer a dengue epidemic prediction using an ML model based on the wind speed, temperature, humidity, and rainfall of climate factors. Historical data from five districts in Selangor, Malaysia is collected and identifies the climatic parameters impacting dengue epidemics. The study investigates the dengue outbreak variable and data cleaningprocess for precise model input.The several ML model forecasts the occurrence of dengue outbreaks based on a binary target variable that enhances the dengue outbreak forecasting's accuracy and efficacy, which leads to an enhancement of public health response and readiness. Health professionals should be able to take preventative measures based on timely information from dengue fever outbreak predictors.

The study [5] utilizes climate factors such as temperature and humidity, that has the highest link with confirmed dengue fever (DF) cases, to build and compare various prediction models for DF transmission in Jeddah, Saudi Arabia. Three nonlinear models SVM, DT regression, and RF regression, and one linear regression were evaluated. The precise model for predicting the suitable DF transmission, and offers enhanced health authorities important information for disease control. The Support Vector Classification (SVC)model has a prediction accuracy of 76%, model outperformed the existing models.

To overcome the enormous demand for time in a prediction tool, Souza et al., 2022suggested an earlier prediction based on the yearly climate data of Brazilian urban centers. The sophisticated data pre-processing method is integrated with contemporary computing tools for signal processing and manifold learning for accurate dengue prediction. This predictive model has an accuracy from 0.72 to 0.80, which ensures an approach with limited public health resources to get the data needed for outbreak analysis. The method proves that the system can successfully forecast dengue with small data.

To develop an early warning system for dengue epidemics, Yip et al., 2022 suggest a Bayesian modeling framework based on their meteorological factors in the Central Region of Malaysia. The Niño indices associated with the El Niño Southern Oscillation (ENSO) are employed for accurately detecting the short-term and long-term dengue outbreaksforecastingand other environmental variables. The model has a considerable rise in dengue incidence related to several variations in sea surface temperature, and a slight correlation with El Niño Modoki impacts. This method provides anearlier outbreak detection and insightful information for efficient dengue management methods.

To predict the dengue outbreaks in Rio de Janeiro, Brazil, Aleixo et al., 2022 suggest an explainable machine learning model for assisting public health management with planning and resource allocation. This model integrates the weather data, and sociodemographic data from the Brazilian Institute of Geography and Statistics (IBGE), and the National System of Information on Notifiable Diseases (SINAN). The gradient boosting decision tree algorithm (CatBoost) is used for training the data to make a precise decision by the rationale underlying the outbreak forecasts with an emphasis on explainability. This study effectively minimizes the impact of dengue epidemics on public health by enhancing readiness and response.

Sarder et al 2022, suggest a Support Vector Machine model for dengue outbreaks in Bangladesh usingclimatic data, with a particular emphasis on essential meteorological variables such as temperature, humidity, and rainfall. The dengue dataset includesdengue cases and climate variables from 2019 to 2021, the researchers employ various supervised ML methods to forecast outbreaks. For training, 30% of data is used for testing, while 70% is used for training. The SVMhas the best prediction accuracy (96.73%)out of all the algorithms examined. This study enhances the dengue epidemic prediction with better planning and control while high transmission time.

Krishnan et al 2022, suggest an implementation of Decision Tree (DT) and Artificial Neural Network (ANN) models to forecast the dengue outbreaks in Kota Bharu using meteorological factors such as humidity, rainfall, and temperature. The ANN model is evaluated with varying numbers of hidden nodes to enhance prediction accuracy. The study compares performance metrics of two models and ends up with the ANN is more effective than the DT in forecasting epidemics. To help governments take proactive measures to promote public awareness about climate change.The affordable dengue outbreak forecasting model with 90% accuracy is suggested by Ismail et al., 2022. It incorporated into an Internet of Things (IoT)--based early warning system based on factors such as environmental, entomological, and epidemiological data. The forecasting techniques as Hierarchical Forecasting, Machine Learning models (ANN, SVM, Random Forest), and Autoregressive Distributed Lag (ADL) are compared. The RF has the highest accuracy of 95%,however, the accuracy dropped to 92% when entomological data was removed. Overall, the early warning system's realistic ground operationalization also needs the placement of many rain gauges in dengue hot sites. To ensure the accuracy of the rainfall data that would be incorporated into the dengue outbreak forecasting model and integrated into the early warning system, it has been suggested that the rain gauges be placed at the dengue hot sites around 3–4 km apart. Because prevention is preferable to cure, this early warning system has the potential to save lives.

Khan et al., 2022 employ a distinct multilayer perceptron NN and decision tree model for enabling the real-time hospital patient data for early dengue epidemic prediction in Bangladesh. The best strategy for anticipating dengue outbreaks and reducing the possible causality is the main goal of this study. The study performance was evaluated using various methods, based on the25 infection rate-related metrics. The Levenberg–Marquardt algorithm has 97.3% accuracy that surpasses the Decision Trees. The approach seeks to improve the public health management and dengue outbreak prediction.

To improve models for predicting epidemic danger, Zhang et al., 2022 suggest the automated machine learning (AutoML) model. Automating the process using a machine learning model becomes more accessible to non-ML specialists without requiring any specialized knowledge. To forecast the epidemic risk utilizing the AutoML, this study extended an already-existing manually created risk analysis model called EPIRISK. TheAutoML model with the BrewAI platform has an accuracy of 77%, which surpasses the machine learning models. This model is more accessible for researchers who lack machine learning skills and streamlines the pandemic risk prediction.

Majeed et al., 2023 suggest a variety of long short-term memory (LSTM) models to forecast the dengue fever cases in Malaysia. The LSTM model utilizes temporal and spatial attention mechanisms. Six distinct LSTM-based models, including SSA-LSTM, combined the spatial attention with stacked LSTM layers were created and compared based on the dengue cases from 2010 to 2016 using demographic, geographic, climatic, and land-use data. The system performance evaluated using prediction errors (RMSE), the SSA-LSTM model has far better value than the other SVM, DT, and ANN models. The study demonstrates that spatial attention might improve the accuracy of dengue predictions in Malaysia.

Shaikh et al., 2023 offer an early-warning system for predicting dengue illness using cutting-edge machine learning and the DL model. The Neighbour Count-based Dragonfly Electric Fish Optimization (NC-DEFO) model is used for feature selectionand data pre-processing techniques such as outlier removal and missing data filling, the model aims to enhance the prediction accuracy. A CNN, ANN, and SVM-based Optimized Ensemble Classifier (OEC) was utilized for processing the optimized features. In addition, the system offers dengue fever and provides medical advice, such as medication prescriptions and preventative measures. The method results show afinding of precision and effectiveness for early dengue diagnosis and treatment.

B. Exploring the Role of Natural, Socioeconomic, and Technological Factors in Dengue Dynamicsand Predictive Modeling

Chen et al., 2020 investigated the spatial and temporal distribution of dengue fever (DF) in Guangzhou and Foshan, China with the highest DF incidence. In the random forest (RF) and the negative binomial regression analysis, the author identifies the natural and socio-economic factors that influence DF outbreaks. The temperature, humidity, and green area are the natural components significant inGuangzhou, while forest coverage played with major role in Foshan. The socio-economic factor influences the foreign visitors and air passenger transport in Guangzhou tourism in Foshan, and the metro development affectsthe China city. The study utilizes the novel differences among the cities, with a greater impact on foreign visitors, the climate of Guangzhou, and overseas tourism in Foshan. This study advances health education for international travelers and metro passengers, and early detection throughbody temperature checks at public facilities. This method aims to improve dengue prevention, early warning, and control efforts.

Cunha et al (2021)evaluate the relationship between dengue incidence and vegetation greenness during the 2010 pandemic based on the 3826 census tracts spread throughout 474 neighborhoodsin Belo Horizonte, Brazil. This study determines how the socioeconomic and environmental factors affect the dengue risk with the satellite-based vegetation data and adjusted for elevation, land cover, population density, socioeconomic vulnerability, and weather patterns. The association varied by socioeconomic vulnerability, and results reflect the vegetation greenness that correlates negatively with a dengue incidence. It is related to negatively highly vulnerable locations and favorable in less vulnerable places. It shows vegetation management that reduces the risk of dengue, in areas that are already at risk. The study enhances the water infrastructure, sanitation, and tree cover as significant interventions for dengue control. These results showcase the vegetation management and infrastructure development to prevent dengue in urban settings.

Francisco et al (2021) innovate the integrated method to address the limitations of conventional statistical models, for comprehending the integrated effects of landscape and climate elements on the mosquito in dengue incidence. The RF model utilizesentomological, epidemiological, and landscape datafor examining the entomological, epidemiological, and landscape data fromMetropolitan Manila during the wet seasons of 2012–2014. The synergistic impacts of those variables are evaluated by the model-based recursive partitioning (MOB) based on the dengue incidence data that, is significantly impacted by the precipitation in densely populated residential and commercial zones. The mosquito occurrence was extremely sensitive to areas with less precipitation and higher residential density. These results showcase thesignificance of targeting vector surveillance in environmentally susceptible areas and combined urban planning and dengue control methods. However, this studyprovides a novel framework for understanding and preventing vector-borne diseases.

Hovos et al (2022) introduce clinical decision-making by integrating autonomous system-based data analysis in dengue management. The evolutionary methods as genetic algorithms are utilized foroffering the individualized treatment and machine learning methodsfor accurate dengue classification. The technology classifies the dengue cases with 98% accuracy by using the datasets from healthcare facilities and recommends the best therapy. The system has better performance than the earlier methods. The system has better adaptability with more jobs for dengue analysis and provides a scalable clinical management result.

Ikerionwu et al (2022) suggest the Convolutional Neural Networks (CNN) model for the automatic detection of malaria parasites in blood films overcome the limitations of existing microscopy methods. The human error in the traditional microscopy technique is overcome by the suggested method that ensures by investigation of various ML models. The suggested model CNN has an excellent accuracy of 99.23% in malaria parasite detection by evaluating the peer-reviewed papers from the most reliable dataset. Overall, this study suggests the ML-driven automation model that effectivelyenhances early detection and diagnosis by minimizing the reliance on human expertise by saving lives.

Kaur et al., (2021)suggest machine learning and neural networks for identifying and detecting the vector-borne infectious disease to end the spread of deadly epidemics. The unchecked population of mosquitoes and arboviruses becomes more and more prevalent for disease spreads through the air. This study examines the previous works with the aims of algorithms, data sources, and performance metrics utilized for the prediction and detection of diseases. This study examines the threats to public health, with therecent developments, challenges, and potential applications of ML and DL techniques advancements. It paves a way to enhance outbreak control through the analysis of methods, data, and variables. Kaur et al., (2022)suggest the individual and ensemble Artificial Intelligence (AI) algorithms utilized for forecasting vector-borne illnesses (VBDs). This study reviews the Aedes, Anopheles, and Culex mosquitovector species from the 159 papers and examines the methods, settings, datasets, and performance metrics used in previous predictive models. The unchecked mosquito population impact and increased air travel on the spread of VBD are identified in the study. The results show a more insightful proof,before incorporating ML and DL models into routine diagnostic procedures. It illustrates each VBD prediction model's VBD values in assisting the patients and healthcare professionals in making medical decisions.

Li et al (2021)employ ML-based regression algorithms and statistical models to comprehend the long-term association between socioeconomic factors and ecological environment impacts of DF from 1998 and 2016in Guangzhou, China. The principal component analysis (PCA) model was utilized for determining the necessary variables such as land use, travel, nighttime light, and population density. The DF cases are predicted using support vector regression, generalized linear models, and ordinary least squares models. The best performance was determined by comparing it with the generalized additive model, which effectively captures extreme outbreaks and non-linear interactions. The study showcases the necessary ecological and socioeconomic factors considered in the DF prevention methods and it offers valuable insight for policy development in endemic regions to enhance the DF control and prevention.

Medina-Ortiz et al (2020) suggest the unsupervised learning techniques of RV-Clustering to enhance the prediction based on non-linear datasets. Non-linear or categorical characteristics are rapidly problematic for existing supervised learning models, that have lower classification or regression performance. The suggested RV-Clustering is employed for identifying the best dataset partitions by deconvoluting the variables and enhancing the model performance than the existing supervised learning models. To prevent overfitting and ensure representativity, the partitions are cross-validated. Various non-linear datasets have been successfully tested by the RV clustering model which yields a greater performance due to its ease of usage and low human input requirements, and its well-suited for the fields of biology, biomedicine, and protein engineering.

Swe et al (2020) developed the supervised learning-based classification model for dengue fever types and cut down therequirements of blood and urine testing of patients. The system classifies the dengue fever categories, such as dengue fever, severe fever, or high-temperature cold fever, depending on the patient's symptoms, using the Support Vector Machine (SVM) and datasets collected from the hospital in Lao PDR. Through a forum, members can exchange case details and gather instructional materials about the dengue disease. The technology is tested using Java which attempts to minimize testing expenses and enhances the diagnostic effectiveness. The system additionally evaluates its effect on the number of instances in the Champpassak region of Lao PDR. The tool enhances the disease classification and patient management.

C. Predictive Models for Dengue Fever Incidence and Outbreak Forecasting

Tanawi, et al., (2021) suggest the Support vector regression (SVR) as a prediction model for the frequency of dengue episodes in the DKI Jakarta. The model utilizes the past dengue incidence data as a predictor variable with the meteorological variables as temperature, humidity, and rainfall. The process employs cross-correlation to evaluate the temporal lag among predictor variables and dengue incidences to determine the pertinent predictors. The system performance was evaluated using the performance metrics as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) and it was compared with theexisting linear and radial kernels models. The results showcase the reliable forecasting of dengue episodes and the linear kernel SVR outperforms than radial kernel. However, this approach provides a trustworthy instrument for early forecasting and outbreak avoidance.

Hoyos et al (2021) suggest a detailed evaluation of three main dengue modeling techniquesintervention, epidemic, and diagnosis. The PRISMA methodology utilized for a Systematic Literature Review (SLR) on 64 papers, can most widely applied method in each field. Logistic regression is known as the most popular model for diagnostic conditions. The epidemic linear regression approach is particularly employed for a geographical analysis. The General Linear Model remains the most common model for modelinginterventions. The difficulties are related to the low-quality healthcare data utilized for the study showing the cause-effect models and the uncertainty management that improve the diagnosis accuracy. Furthermore, federated learning is utilized for enhancing the data security for model creation, decentralizing data processing, and reducing computational costs.

Metelmann et al (2021) proposed a delay differential equation model for predicting the Aedes albopictus mosquitoes' function and temperature-dependent growth in dengue spread in China's mainland. The integration of temperature effects on virus replication and mosquito growth, this model replicates mosquito population dynamics and detects the mosquito occurrence areas with great accuracy. Based on the report, the Guangzhou dengue outbreak in 2014 might be lasted an extra four weeks when the mosquito control measures hadn't been taken. According to the model, dengue can spread throughout southern China for more than seven months each year, while in hot summer months, in the northern areas such as Beijing, dengue can spread. To precisely forecast the risks of dengue transmission over several climatic zones, this study illustrates theneed for comprehensive vector and infection ecology.

Zhao et al (2020) suggest the comparison of weekly dengue case predictions using the artificial neural network (ANN) model with RF in Colombia. The department level and the national level of RL are created and combined for performing the forecasting of errors raised with the forecast horizon lengths. The national-level RF model performed more precisely than the local-level model. The sociodemographic indicators are crucial for longer-term forecasts, and the environmental predictors as temperature and precipitation become more important forshort-term projections. This study demonstrates the RF with a focus on nationally pooled crucial models and sociodemographic data for better dengue forecasting.

Lim et al (2020) suggest the extreme value theory (EVT) techniques for extreme dengue epidemics in Thailand. This utilizes 25 years of province-level dengue data from 1993 to 2018. Based on eight other benchmarks, this study compared the inhomogeneous point process (IPP) approach that discovered the best performance by providing consistent parameters and trustworthy distributional properties. Future dengue outbreaks might surpass the past maximums, based on the IPP model, with notable regional variations. The results of EVT mighthelphealth planners control the likelihood of severe dengue outbreaks. Other infectious diseases have been observed over extended periods that have also been investigated using this method.

Gangula et al., (2023)suggest the hybrid ensemble machine learning method for identifying the critical factors affecting the dengue disease spread. This study showcases the impacts of climate variables like temperature, humidity, and precipitation on the disease spread. The predictive model'sperformance is analyzed for dengue spread which is improved using severalML algorithms. The results highlight theimportant characteristics related to dengue transmission and enhance the forecasting model accuracy. The method has apromisingresult and the cutting-edge machine learning model is suitable for dengue and other mosquito-borne illnesses.

Salim et al (2021)suggest machine learning models, particularly Support Vector Machine (SVM) with a linear kernel model for forecasting dengue outbreaks in Selangor, Malaysia based on climate variables such as temperature, wind speed, humidity, and rainfall. The SVM model with enhanced sensitivity and accuracy of 70% while employing the balanced data. In the model, the week of the year was found to be the most significant predictor. The study employs a potential ML modelfor forecasting dengue outbreaks and recommends more research into nature-inspired or boosting algorithms for upcoming models.

Navarro Valencia et al., (2021) suggestan examination of the relationship among the dengue incidence in Panama from 1999 to 2017 and meteorological factors such as air temperature, precipitation, and relative humidity. To anticipate dengue outbreaks, it assesses the predictive capabilities of the recurrent neural network (RNN-LSTM) model andSARIMA and SARIMAX regression models. The results showcase the weak but statistically improved relationship among dengue cases and climate variables. The RMSE and MAPE values showcase their efficiency in forecastingfuture outbreaks, and the SARIMAX and RNN-LSTM models have comparable performance. The study becomes a more significantsystem for early alert systems of dengue in tropical areas.

Da Costa et al (2024) address challenges of bimodal data distributions, that are rapidly found in epidemiologicalinvestigations using the unique bimodal regression model based on the log-generalized odd log-logistic exponential distribution for the dengue case data analysis. In contrast, theexisting unimodal models enhance the flexibility and accuracy while capturing the intricate illness patterns. The regression analysis model has betterdetection of the disease rate of2022 Federal District dengue data from Brazil. The Monte Carlo simulations model is utilized for a maximum likelihood estimation and the model's parameters to confirm its accuracy. Overall, this model's performance has better data and higher verification for wider applicability.

Zeng et al (2024) evaluate the return period (RP) and return level (RL) of dengue fever (DF) outbreaksfrom 1978 and 2021in Guangdong, China.The lognormal distribution, the normal distribution, and the generalized logistic distribution model are employed. These models are intended to assist in the development of methods for DF outbreak prevention and control. The model performance was analysed using R2, RMSE, and AIC metrics for evaluating the models' goodness of fit. The forecasts show Guangdong with a DF outbreak that surpasses historical maximums in 35–36 years and a DF epidemic that is higher than the 2019 peak in 4–5 years. The research showcases the temporal regularity ofDF outbreaks and the model is effective for accurately predicting such occurrences.

D. Literature Research on Machine Learning and Dengue

A detailed evaluation of several studies covering the diagnosis, treatment, prediction, policy, and dengue detection model is shown in Table 1. The majority of research on risk assessment, and prediction with no confirmation. The mobility and climate data play a crucial role in dengue prediction.

Table 1. Comparative analysis of various ML models

Reference Work	Methodology	Feature(s)/Dataset Used
Gangula et al., 2023	Hybrid ensemble machine learning integrates Bagging, Boosting, Voting, and weak learners.	The dataset consists of features such as fever, bleeding, myalgia, glandular swelling, fatigue, and diagnosis results (positive/negative).
Khan et al.,2023	Machine learning algorithms such as Decision Tree (DT), Random Forest (RF), and Naive Bayes (NB),presumptive diagnosis system (PDS) for early dengue fever detection.	400 records of 15 attributes.
Sood et al., 2023	Naive Bayesian Network (NBN) for diagnosingdengue virus and generating real-time alerts.	Global Positioning Systems (GPS)-based global risk assessment
Gupta et al.,2023	TheKNN classifier, decision tree, random forest, Gaussian naive Bayes, and support vector classifier (SVC) for fast detection and prognosis of dengue disease.	DengAI: Predicting Disease Spread
Islam et al.,2024	Prophet model for forecasting future Dengue outbreak	Mid-May to Late October outbreak predictionswith the government's exposed data.
Meileni et al., 2024	Application of Support Vector Machines (SVM) in Geospatial Artificial Intelligence for dengue fever prediction.	environmental factors influencing disease spread, with Geospatial and real-time data processing
Mazhar et al., 2024	Machine learning-based prediction of dengue outbreaks.	Climatic factors, including temperature, rainfall, relative humidity, and wind speed, along with monthly records of dengue cases.
Sebastianelli et al., 2024	The ensemble approach integrates CatBoost, SVM, and LSTM models for DIR forecasting in Brazil and Peru.	Satellite-based products, socio-economic variables, and historical DIR data.
Nasir et al., 2024	AI and machine learning for dengue prediction.	Climatic variables (sun exposure, temperature, humidity, wind speed, and precipitation) in Bandung City. The data was extracted from Indonesia's Ministry of Health and the Meteorological, Climatological, and Geophysical Agency.
Lu et al., 2025	The MLR, LSTM, and SI-SIR models used for dengue forecasting	climate variables (temperature, humidity, precipitation) and mosquito biting rate for forecasting dengue incidence in Selangor, Malaysia.

Dengue fever epidemiology, dengue hemorrhagic fever (DHF), pathogenesis of DHF, and clinical manifestations are categorized into severe dengue, with and without dengue warning symptoms. Intelligent systems employed for dengue prediction and management strategies. Mostly, intelligent prediction models and proactive management strategies greatly enhance dengue fever's early detection and effective mitigation. This might reduce the impact of Dengue Fever on healthcare systems and public health.

E. Future Work

Future work should concentrate on enhancing the generality and precision of ML models for dengue prediction by integrating several real-time data, including satellite images, mobile health data, and cutting-edge meteorological forecasts. Prediction capabilities should be improved by advanced research with adeep learning method, such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networksin areas with sparse data availability. Furthermore, the advanced proactive outbreak monitoring might be possible by the integration of artificial intelligence (AI) and Internet of Things (IoT) sensors for real-time surveillance. To guarantee a predictive methodology, that is integrated with anational disease management strategy, policy development should prioritize the AI-driven systems implementation in public health frameworks. Governments should set rules related to data privacy and morality while using climate and health data.To employ sophisticated prediction models, funds need to be set aside for infrastructural and human resource capacity building. To build ascalable solution, collaboration among researchers, technology, and public health authorities will be essential. Finally, to address the regional nature of dengue and improve the overall global response capacities, policies should promote cross-border data sharing.

III. CONCLUSIONS

This study concludes by highlighting the potential of machine learning (ML) models in managing and forecasting dengue epidemics and highlighting the significance of integrating the sociodemographic, environmental, and meteorological aspects. Through an investigation of several machine learning methodologies and their implementations, the predictive models have substantial potential for precise predictionof dengue epidemics. Moreover, real-time data, such as satellite images and IoT-based sensors, and new risk variables can efficiently enhance the accuracy and timeliness of forecasts.The results show a need to improve the models to boost their dependability even in areas with small data. Additionally, the study promotes the incorporation of AI-powered systems into the public health infrastructures, prioritizing accessibility and scalability for resource-constrained regions. The guidelines enhance the ethical utilization of data and facilitate collaboration among the governments, healthcare providers, and researchers are urged to adopt by policymakers. Overall, the machine learning model employed for forecasting dengue is acrucial first step toward more effective disease control, which will ultimately enhance public health outcomes and lessen the effects of epidemics.

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