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Review Article

Smart Healthcare Framework for Chikungunya Surveillance Using Machine Learning

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A B S T R A C T

Chikungunya virus (CGN) is a mosquito-borne alphavirus responsible for causing significant outbreaks characterised by fever, severe joint pain, rash, and long-lasting arthralgia, impacting millions worldwide. Despite its clinical similarity to other arboviral infections, early and accurate diagnosis remains critical for effective patient management and outbreak control. This paper presents a comprehensive review of CGN's epidemiology, transmission dynamics, and monitoring challenges. Furthermore, it explores the recent advancements in digital health, technologies specifically the integration of Internet of Things (IoT) devices and Artificial Intelligence (AI) to enhance real-time detection, monitoring, and epidemiological surveillance of CGN. These innovations offer promising avenues for early warning systems, improved vector control strategies, and data-driven public health interventions. By harnessing digital tools, healthcare systems can achieve more efficient outbreak responses, reduce disease burden, and better protect vulnerable populations. This study underscores the imperative for multidisciplinary approaches combining cutting-edge digital technologies to combat emerging arboviral threats like Chikungunya.

Keywords: Machine Learning, Time Series, Arima Model, Public Health

Introduction

Chikungunya fever (CGN) is a re-emerging, mosquito-borne viral disease caused by the Chikungunya virus (CGN), an enveloped, positive-sense, single-stranded RNA virus of the Togaviridae family. Transmitted predominantly by Aedes aegypti and Aedes albopictus mosquitoes, CGN has spread globally over the past two decades, triggering widespread epidemics in Africa, Southeast Asia, India, Europe, and the Americas.[1] The World Health Organization (WHO) classifies CGN as a priority pathogen due to its rapid

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spread, epidemic potential, and the absence of effective antivirals or licensed vaccines. WHO reports indicate that, as of 2023, more than 2.9 million suspected cases have been documented in the Americas alone between 2013 and 2023.[2] Clinically, CGN is characterised by the sudden onset of high-grade fever, severe polyarthralgia, headache, rash, myalgia, and fatigue. Although the acute phase typically resolves within 7–10 days, a significant proportion of patients up to 60% in some studies develop chronic joint pain or arthritis that may persist for months or even years. The pathophysiological basis of these chronic symptoms involves persistence of the virus in host macrophages and joint tissues, along with a dysregulated immune response, resulting in sustained inflammation.[3] Current diagnostic methods include reverse transcriptase polymerase chain reaction (RT-PCR), serological assays (e.g., IgM/IgG ELISA), and viral isolation. However, limited availability, high costs, and delayed turnaround times hinder early detection and effective outbreak response in many endemic regions. Although several vaccine candidates are in advanced stages of clinical trials, none have yet received licensure for public use.[4] A critical factor contributing to the global expansion of CGN is its capacity for genetic adaptation. Mutations in the viral E1 glycoprotein have enhanced CGN's replication efficiency in Aedes albopictus, facilitating transmission in temperate climates and thereby contributing to larger-scale outbreaks in regions previously considered non-endemic.[5] Figure 1 shows the basic symptoms of Chikungunya virus. Mosquitoes are among the deadliest vectors globally, responsible for transmitting a variety of viral and parasitic diseases that significantly impact human health. Prominent mosquito-borne diseases include Chikungunya, dengue, Zika virus, and malaria, each with unique transmission patterns, clinical features, and epidemiological profiles.

These diseases are primarily spread by Aedes aegypti, Aedes albopictus, and Anopheles mosquitoes, depending on the pathogen involved. Rapid urbanisation, climate change, and increased global travel have accelerated the spread of these vectors into previously unaffected regions. Chikungunya fever (CGN), in particular, is caused by the Chikungunya virus (CGN) and is characterised by high fever and debilitating joint pain. Table 1 represents the comparison with mosquito-borne diseases. A critical public health consequence of climate change is the expanding geographic range and rising transmission of vector-borne diseases (VBDs). Because arthropod vectors like mosquitoes and ticks are ectothermic, key biological factors, including their survival rates, reproductive output, and vector competence, are acutely sensitive to shifts in ambient temperature and humidity.[6]

Unlike dengue, CGN rarely causes haemorrhagic complications, but long-term joint issues are common. The Zika virus is linked to birth defects, while malaria is caused by Plasmodium parasites and can be life-threatening if untreated. These diseases pose a major challenge to public health systems in endemic and emerging regions. As such, understanding their differences is crucial for targeted surveillance, diagnosis, and intervention strategies.

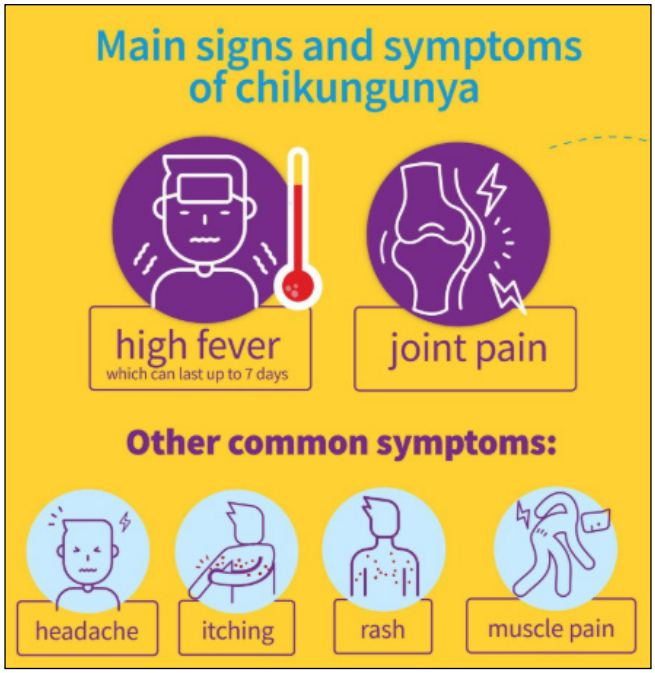


Figure 1.WHO- guided symptoms of Chikungunya

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Table 1.Chikungunya with Other Mosquito-Borne Diseases

Symptoms	Chikungunya	Dengue	Zika	Malaria	Yellow Fever
Causative	CGN	DENV	ZIKV	Plasmodium	Yellow fever
Mosquito	Aedes aegypti, Ae. Albopictus	Aedes aegypti, Ae. albopictus	Aedes aegypti, Ae. albopictus	Anopheles species	Aedes aegypti
Fever	High-grade	High-grade	Mild	Mild	High
Joint Pain	Severe	Mild	Mild	No	No
Rash	Common	Common	Common	Rare	Possible

Methodology

This study adopts a structured literature survey methodology to review, analyse, and synthesise current knowledge on Chikungunya virus (CGN) infection, its clinical progression, diagnostic challenges, epidemiology, and recent advancements in monitoring through digital health technologies. The methodology was designed to ensure comprehensive coverage, relevance, and scientific rigour. Figure 2 shows the conceptual data flow.

- **Research Design:** A qualitative literature review was employed to identify key research trends, findings, and gaps in Chikungunya-related research. The review also integrates emerging IoT-based surveillance, remote monitoring systems, and AI-assisted diagnostics to explore how technology is transforming public health responses.
- **Data Sources**: The following databases were searched: PubMed, Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. Relevant reports from the World Health Organization (WHO) and the Centers for Disease Control and Prevention (CDC) were also reviewed. The search strategy includes various keywords “Chikungunya”, “CGN”, “arboviral diseases”, “diagnosis”, “Aedes aegypti”, “Aedes albopictus”, “IoT in healthcare”, “smart monitoring”, “digital health”, and “early detection”.

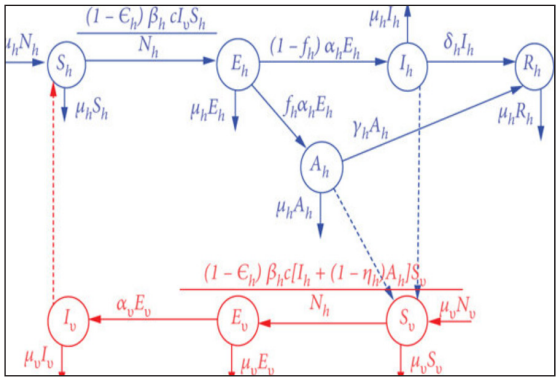


Figure 2.Mathematical flow diagram

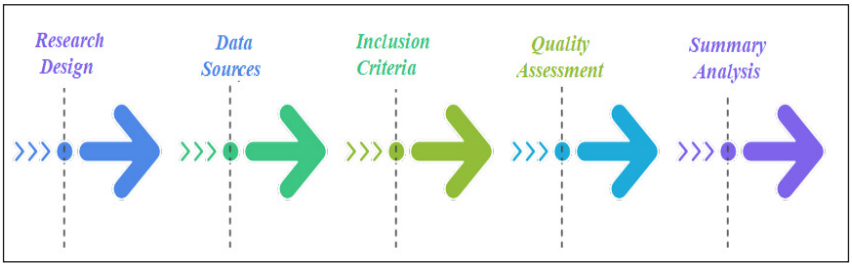


Figure 3.Represents the conceptual flow of data

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Literature Survey

This literature review section provides an overview of key articles on infectious disease control. The survey compiles pivotal research studies on the dynamics and impacts of the Chikungunya virus. It encompasses investigations of environmental influences, such as rainfall and temperature, on the virus's spread and global epidemiological studies that underline the significant role of international travel in virus dissemination. Additionally, the surveillance studies emphasise the critical need for enhanced monitoring and timely public health responses. Furthermore, a dedicated subsection highlights recent advancements in IoT and cloud computing as they pertain to healthcare systems. The literature survey is related to two major parts: chikungunya virus and smart healthcare systems.

Chikungunya Virus Type

Numerous studies have investigated the dynamics, transmission patterns, and control measures of the Chikungunya virus (CGN) across different geographic and climatic contexts. Research has highlighted the significant impact of environmental factors such as rainfall and temperature on mosquito proliferation and CGN outbreaks, especially in tropical regions like Thailand and Sub-Saharan Africa. The insect vectors responsible for major diseases include malaria, filaria, leishmaniasis (kala-azar), dengue, chikungunya, and Zika. To monitor these populations, public health entomologists and researchers conduct routine vector surveillance. Population density for both target vectors and non-target species is primarily measured by catch-per-unit-time. Historically, in malaria control operations, this standard began with sampling resting mosquitoes during peak dawn and dusk periods.[7] Chadsuthi et al.[8] analysed how temperature and rainfall influenced the spatial spread of chikungunya during the 2008–2009 outbreaks in Thailand. The study used spatial statistical models to link climate variables with case distribution. It emphasised that increased rainfall led to more mosquito breeding sites. The results highlighted the role of climatic conditions in epidemic patterns. This provides a foundation for climate-based outbreak prediction models. Javelle et al.[9] assessed chikungunya risk among travellers to Thailand during a major outbreak. Surveillance data revealed a significant rise in imported cases among European tourists. The study underlined the need for better travel advisories and vector control. It also emphasised the global implications of regional outbreaks. Their findings stress the importance of surveillance during peak tourist seasons. Khongwichit et al. [10] reported a major chikungunya outbreak in Thailand (2018–2019), affecting over 10,000 people. Molecular epidemiology revealed ECSA genotype dominance. The study provided insights into viral evolution and transmission patterns. It stressed the need for strengthened public health responses. High mobility and vector abundance were identified as key contributors. Alade et al.[11] presented a mathematical model incorporating adaptive immune response to describe chikungunya virus dynamics within a host. The model captures both viral replication and immune suppression. Simulation results were validated using biological data. Their work helps understand immune kinetics in infections. It supports drug development and immune-targeted therapies. Gozzer et al.[12] evaluated the economic burden of chikungunya outbreaks in Latin America and the Caribbean. The study reported significant direct and indirect cost, including healthcare expenses and productivity loss. They advocated for cost-effective vector control interventions. Economic models demonstrated potential cost savings via early detection. It highlights the need for financial preparedness in epidemic settings. Rojas et al.[13] conducted field surveillance in urban and rural Colombia to detect chikungunya virus presence. Using RT-PCR and mosquito trapping, they confirmed active transmission. The study found higher incidence in urban areas. It recommended differential intervention strategies based on geography. This supports rural-urban tailored public health planning.

Smart Healthcare Systems Using Machine Learning

Parallel to the study of infectious diseases, recent literature has focused on the application of smart technologies in healthcare delivery and disease prevention. Digital Twin (DT), Internet of Things (IoT), edge computing, and fuzzy logic-based systems are being increasingly employed for real-time health monitoring and predictive diagnostics. Studies have demonstrated the use of DTs for personalised and context-aware healthcare systems, especially for chronic disease and dengue fever prediction. In addition, security and trust in health data communication remain critical issues, prompting the development of encrypted routing schemes and explainable AI methods.[14] Golden Nancy et al. proposed a Digital Twin framework for improving personalised healthcare and respiratory health monitoring. The framework creates virtual representations of patients using healthcare records, treatment information, and real-time sensor data. An LSTM-based machine learning model is employed to predict patient health conditions and nutritional requirements. The system supports personalised treatment planning and proactive healthcare interventions through continuous monitoring.[15] Elayan et al. introduced a digital twin framework for intelligent and context-aware IoT healthcare systems. The framework uses digital twin technology to represent patients and integrate physiological and contextual healthcare information. Machine learning techniques are incorporated to support continuous patient monitoring and intelligent health-condition analysis.[16] Islam and Bhuiyan developed an integrated and scalable

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framework for cloud- and IoT-based green healthcare systems. Cloud computing is utilised for healthcare data storage, processing, accessibility, and communication. Hierarchical clustering is applied for data identification and analysis within the proposed healthcare environment.[17] Singh and Chatterjee proposed a secure health-monitoring framework based on edge computing for electronic healthcare systems. The framework processes healthcare data closer to the user to reduce response time and dependence on centralised cloud infrastructure. Edge computing is combined with IoT technologies for efficient monitoring and analysis of physiological data. Attribute-based encryption is employed to provide secure access and protect sensitive healthcare information. The proposed framework achieves high diagnostic performance while addressing security, privacy, and real-time processing requirements.[18] Hosseinzadeh et al. developed a fuzzy logic-based secure hierarchical routing scheme using the firefly algorithm for healthcare IoT networks. The proposed FSRF framework combines fuzzy trust evaluation, Firefly-based clustering, and inter-cluster routing. Fuzzy logic is used to evaluate the trustworthiness of IoT devices and identify potentially malicious nodes. The framework addresses routing threats such as black-hole, flooding, wormhole, sinkhole, and selective-forwarding attacks.[19] Chen et al. presented a systematic review of process mining and data mining applications for chronic disease management. The study examined research using data-driven techniques for diagnosis, risk assessment, patient monitoring, and healthcare management. Process mining can identify patterns and inefficiencies in clinical workflows and patient-care pathways. Data mining techniques support patient stratification, predictive analysis, and evidence-based healthcare decision-making.[20] Sood et al. proposed an intelligent healthcare system for predicting, monitoring, and preventing dengue virus infection. The system integrates IoT, cloud computing, and fog computing to support continuous collection and processing of healthcare information. It identifies and monitors potentially infected individuals and provides alerts to relevant stakeholders. The framework supports diverse medical IoT applications. Purnomo & prediction enable efficient medical response. Weighted random forest enhances classification accuracy. The approach reduces latency and supports edge-level analytics.

Table 2.Represents the various studies regarding smart healthcare systems

Author	Methodology	Key Findings
Golden Nancy et al.[14]	Digital Twin framework integrated with IoT and machine learning for respiratory healthcare and patient monitoring	Supported personalized healthcare, continuous monitoring, and proactive health-condition prediction
Elayan et al. [15]	Digital Twin-based intelligent, context-aware IoT healthcare framework with AI/ML for health monitoring	Improved context-aware monitoring, predictive analysis, and intelligent healthcare decision-making
Islam & Bhuiyan [16]	Scalable cloud-IoT framework for green healthcare with wearable sensors and cloud-based data processing	Enhanced real-time patient monitoring, healthcare data accessibility, scalability, and energy-efficient healthcare services
Singh & Chatterjee [17]	Edge computing-based secure healthcare framework using IoT and Attribute-Based Encryption (ABE)	Enabled secure, low-latency, and real-time healthcare data processing while protecting patient information
Hosseinzadeh et al. [18]	Fuzzy logic-based secure hierarchical IoT routing using the Firefly Algorithm and trust evaluation	Improved routing security, energy efficiency, reliability, and protection against malicious network attacks
Chen et al. [19]	Process mining and data mining techniques for chronic disease management and healthcare workflow analysis	Demonstrated the effectiveness of data-driven methods for patient stratification, risk assessment, prediction, and chronic disease management
Sood et al. [20]	Intelligent healthcare system integrating IoT, cloud, and fog computing for dengue prediction and prevention	Supported real-time dengue surveillance, early prediction, continuous monitoring, and timely healthcare intervention

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Challenges & Future Directions

Phase I: Data Availability and Quality Constraints: The effectiveness of Artificial Intelligence (AI) models for Chikungunya disease detection is fundamentally dependent on the availability of high-quality, labelled, and heterogeneous datasets. However, existing datasets are often sparse, region-specific, and inconsistently annotated, limiting model generalisation across diverse geographical and epidemiological settings. The absence of standardised data repositories significantly impedes the development of robust and transferable AI-driven diagnostic and surveillance systems.

Phase II: Epidemiological and Environmental Dynamics: Chikungunya transmission is strongly influenced by environmental variables such as temperature, rainfall, humidity, and vector density. Accurate outbreak prediction therefore requires AI models capable of integrating dynamic spatiotemporal environmental data. This necessitates the fusion of epidemiological data with IoT-enabled sensor networks and satellite-based remote sensing systems to capture real-time environmental variations and vector breeding patterns.

Phase III: Real-Time Monitoring and Temporal Sensitivity: The establishment of a time-sensitive remote monitoring framework is critical for continuously evaluating the status and progression of Chikungunya virus (CHIKV) infections.

Phase IV: Technological and Infrastructure Limitations: Although IoT-based frameworks have been proposed for large-scale public health monitoring, their practical deployment in resource-constrained regions remains limited. Challenges such as inadequate network connectivity, high implementation costs, and limited technical expertise restrict the scalability and sustainability of IoT-driven Chikungunya surveillance systems in low- and middle-income settings.

Phase V: Security, Privacy, and Ethical Considerations: With increasing digitisation and the adoption of IoT–cloud infrastructures for disease surveillance, concerns related to data security, patient privacy, and ethical governance become increasingly critical. Ensuring secure data transmission, privacy-preserving analytics, and compliance with regulatory frameworks is essential to building trust and facilitating widespread adoption of AI-enabled Chikungunya monitoring solutions.

Results

Conventional epidemiological surveillance remains important; however, recent studies increasingly incorporate Artificial Intelligence (AI), Internet of Things (IoT), mathematical modeling, and Digital Twin (DT) technologies to improve the timeliness and accuracy of disease monitoring. The reviewed studies indicate that AI-based approaches can identify complex relationships among clinical, environmental, and epidemiological variables, thereby supporting early disease classification and outbreak prediction. Table 3 presents a comparative assessment of commonly applied computational models. Among the evaluated approaches, Artificial Neural Network (ANN) achieved the highest reported accuracy of 92%, followed by Decision Tree with 85% and ARIMA with 78%. ANN demonstrated a strong capability in learning nonlinear relationships and was primarily applied to disease classification and outbreak prediction. Decision Tree models provided comparatively lower predictive accuracy but offered advantages in terms of interpretability and computational simplicity. ARIMA models were mainly utilized for temporal forecasting and demonstrated effectiveness in capturing seasonal and time-dependent patterns in Chikungunya incidence.

Conclusion

This survey critically reviews and synthesises multidisciplinary research spanning epidemiology, mathematical modelling, and intelligent computational paradigms, highlighting the transformative potential of Artificial Intelligence (AI), Internet of Things (IoT), and Digital Twin (DT) technologies in advancing next-generation disease surveillance, forecasting, and intervention frameworks. The convergence of IoT-enabled real-time sensing infrastructures with edge-cloud computing architectures has substantially enhanced continuous health monitoring, early outbreak detection, and data-driven clinical decision support. Moreover, the integration of Explainable Artificial Intelligence (XAI), fuzzy inference systems, and metaheuristic optimisation techniques—including Firefly and Whale Optimisation algorithms—has contributed to improved interpretability, robustness, and computational efficiency of AI-based healthcare models. Digital Twin technology has emerged as a disruptive paradigm, enabling virtual representations of patient-specific and population-level health dynamics to support infection risk stratification, personalised treatment planning, and optimised care delivery pathways.

Table 3.Comparison of ANN, Decision Tree, and ARIMA Models

Model	Application	Accuracy	Model	Limitation of model
ANN	Disease classification and outbreak prediction using nonlinear patterns	92	High predictive power	Requires large training data and high computation
Decision tree	Classification based on symptoms/ features	85	Simple, interpretable, fast training	Overfitting may occur with deep trees

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Arima model	Time-series forecasting of chikungunya	78	Effective for seasonal outbreak prediction	Not suitable for feature-based classification tasks

Despite these advances, several critical challenges remain unresolved. These include persistent concerns related to data privacy, security, and ethical governance; interoperability limitations across heterogeneous sensing, clinical, and analytical platforms; the lack of standardised, high-quality datasets for reliable AI training and validation; and the limited generalisability of predictive models across diverse geographic, climatic, and socio-economic settings. Furthermore, the adoption of intelligent surveillance and decision-support systems in low-resource environments continues to be impeded by infrastructural deficiencies, economic constraints, and gaps in digital literacy. Addressing these challenges is imperative for the development of scalable, trustworthy, and equitable AI-driven frameworks for global Chikungunya surveillance and management.

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