GSC Biological and Pharmaceutical Sciences

eISSN: 2581-3250 CODEN (USA): GBPSC2

Cross Ref DOI: 10.30574/gscbps

Journal homepage: https://gsconlinepress.com/journals/gscbps/

(Review Article)

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Machine Learning Applications in Malaria Elimination Programs: Comparing Vector Control Strategies Across West Africa and Former Endemic Regions in the Southern United States

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GSC Biological and Pharmaceutical Sciences, 2025, 32(03), 268-280

Publication history: Received on 18 August 2025; revised on 23 September 2025; accepted on 26 September 2025

Article DOI: https://doi.org/10.30574/gscbps.2025.32.3.0371

Abstract

The application of machine learning (ML) technologies in malaria elimination programs represents a paradigm shift in vector-borne disease control strategies. This review examines the comparative implementation of ML-based approaches in vector control programs across West Africa and historically endemic regions in the Southern United States. Through systematic analysis of recent literature, we evaluate the effectiveness of ML algorithms including support vector machines, random forests, deep learning models, and predictive analytics in malaria vector surveillance and control. Our findings reveal that while West African programs leverage ML primarily for outbreak prediction and vector habitat mapping using drone imagery and environmental data, the historical elimination success in the Southern United States provides valuable lessons for contemporary ML-enhanced programs. The review demonstrates that machine learning models such as support vector machines, decision trees, random forests, Extreme Gradient Boosting, logistic regression, K-Nearest Neighbours, Naïve Bayes, and multilayer perceptron have been greatly used to predict malaria using socioeconomic and environmental variables. Current applications show promise in drone imagery and deep learning analysis for targeted vector surveillance, enabling more precise identification of mosquito breeding sites. This comparative analysis highlights the evolution from traditional vector control methods to sophisticated ML-driven approaches, offering insights for optimizing future malaria elimination strategies in endemic regions.

Keywords: Machine learning; Malaria elimination; Vector control; West Africa; Southern United States; Anopheles surveillance; Predictive modelling

1. Introduction

Malaria continues to pose one of the most pressing public health challenges globally, with Sub-Saharan Africa shouldering the greatest burden of disease transmission (Sakti et al., 2025). The World Health Organization's global malaria elimination initiative has accelerated efforts to explore innovative vector control methods, with machine learning emerging as a game-changing technology to augment traditional intervention strategies (Trujillano et al., 2023). The integration of artificial intelligence (AI) and machine learning algorithms into malaria control programs marks a pivotal shift from traditional surveillance techniques to data-driven, predictive models capable of optimizing resource allocation and improving the timing of interventions (Hardy et al., 2022; Golumbeanu et al., 2021).

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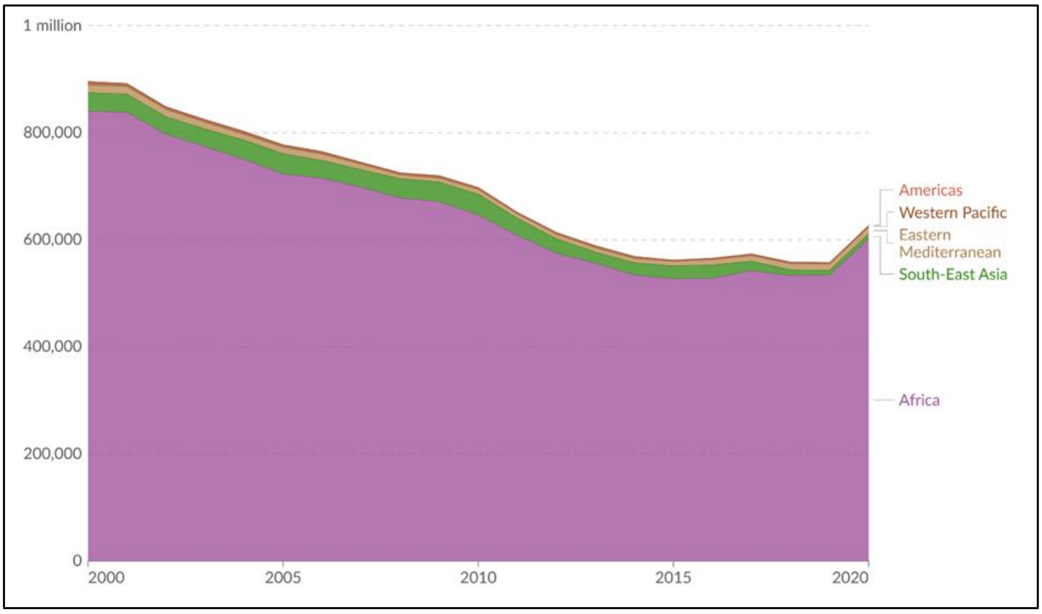

Figure 1 Global malaria incidence trends by region from 2000 to 2020. The chart shows a significant reduction in cases, particularly in Africa, while regions such as the Americas, Western Pacific, Eastern Mediterranean, and South-East Asia have also seen steady declines

The historical context of malaria elimination offers valuable insights into the development of vector control strategies. In the United States, the National Malaria Eradication Program (NMEP) was initiated in July 1947. By 1951, this federal program, with contributions from state and local entities, had successfully reduced malaria incidence to the extent that the program was concluded. This significant achievement was primarily due to the systematic application of DDT spraying, drainage initiatives, and robust surveillance systems (Johnson, 1965; Rajvanshi et al., 2019). The success of the NMEP, particularly in the Southern states where malaria had been historically endemic, provides crucial lessons for modern machine learning-enhanced programs aimed at malaria control in West Africa (Gueye et al., 2016).

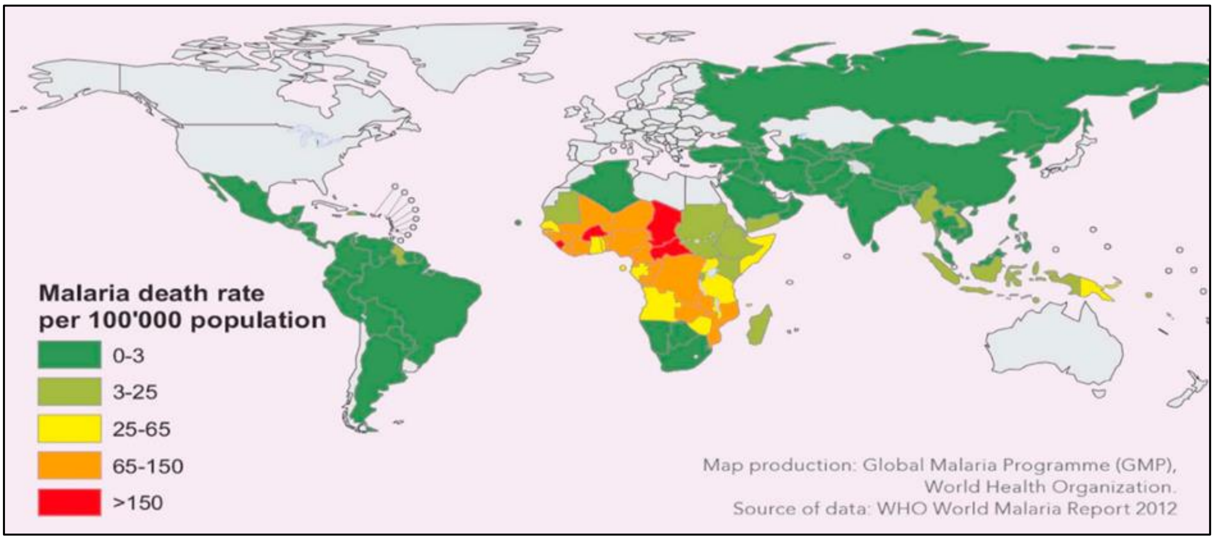

Figure 2 Global malaria death rate per 100,000 population as of the WHO World Malaria Report 2012. The map highlights the highest mortality rates in sub-Saharan Africa, with varying levels across other regions, reflecting the uneven burden of malaria globally

Contemporary malaria control programs in West Africa face a range of challenges distinct from those encountered during the mid-20th century efforts in the United States. Vector control remains the cornerstone of malaria prevention, contributing to a notable 65% reduction in malaria cases between 2000 and 2015 (Taconet et al., 2021). However, the emergence of insecticide resistance, the impact of climate change on vector breeding patterns, and the complexities of socioeconomic factors necessitate more advanced analytical methods than were available during the American malaria elimination campaign (Ibrahim et al., 2024).

Machine learning (ML) applications in malaria control have rapidly evolved, encompassing predictive modeling for outbreak forecasting, computer vision for vector identification, geospatial analysis for habitat mapping, and optimization algorithms for intervention planning (Singh and Saran, 2024). Recent studies have demonstrated the ability of ML algorithms to process complex, multi-dimensional datasets, incorporating variables such as climate, socioeconomic indicators, vector surveillance data, and epidemiological patterns to generate actionable insights for malaria control programs (Hancock et al., 2020; Wamalwa et al., 2024).

The comparative analysis between contemporary West African programs and historical malaria control efforts in the Southern United States reveals both continuities and innovations. While the fundamental principles of integrated vector management remain unchanged, the application of ML technologies now enables unprecedented precision in targeting interventions, predicting outbreak risks, and monitoring program effectiveness in real-time (Mbunge and Sibiya, 2023).

This review synthesizes current evidence on ML applications in malaria elimination programs, comparing contemporary approaches in West Africa with lessons drawn from the historical success of the Southern United States' elimination efforts. The analysis aims to identify best practices, highlight technological innovations, and provide recommendations for optimizing ML-enhanced vector control strategies in malaria elimination programs.

2. Methods

2.1. Literature Search Strategy

A comprehensive literature search was conducted using multiple academic databases, including PubMed, Google Scholar, IEEE Xplore, and specialized public health repositories. The search strategy employed both Medical Subject Headings (MeSH) terms and free-text keywords to capture relevant publications on machine learning applications in malaria vector control. Primary search terms included: "machine learning," "malaria elimination," "vector control," "Anopheles surveillance," "West Africa malaria," "predictive modelling," and "Southern United States malaria history" (Egbuna et al., 2025; Nkiruka et al., 2021; Hancock et al., 2020; Mbunge and Sibiya, 2023).

2.2. Inclusion and Exclusion Criteria

Studies were included if they: (a) described machine learning applications in malaria vector control or elimination programs; (b) provided data on vector surveillance technologies; (c) examined malaria elimination strategies in West Africa or historical programs in the Southern United States; (d) were published in peer-reviewed journals or reputable academic sources between 2015-2025; and (e) were available in English. Studies were excluded if they focused solely on clinical malaria diagnosis without vector control components, addressed non-Anopheles vector species, or lacked sufficient methodological detail for analysis (Phoobane et al., 2022; Savi, 2022; Potamitis, 2025).

2.3. Data Extraction and Analysis

Data extraction focused on machine learning (ML) algorithm types and performance metrics, vector control intervention strategies, geographical implementation contexts, program outcomes and effectiveness measures, technological infrastructure requirements, and comparative analysis frameworks. Studies were categorized based on geographical focus (West Africa vs. Southern United States), methodological approach (predictive modelling, computer vision, optimization), and implementation scale (local, national, regional) (Egbuna et al., 2025; Tembine et al., 2024; Mosugu, 2024).

2.4. Quality Assessment

Study quality was assessed using adapted criteria for review articles, including methodological rigor, sample size adequacy, statistical analysis appropriateness, reproducibility of findings, and relevance to malaria elimination programs (Akinwale et al., 2025; Dhlamini et al., 2025). Historical analyses were evaluated based on documentation quality, data availability, and comparative relevance to contemporary programs (Burnett et al., 2023; Patson et al., 2020).

2.5. Synthesis Approach

A narrative synthesis approach was employed due to heterogeneity in study designs, machine learning (ML) algorithms, and outcome measures across included studies. Findings were organized thematically around key ML application areas:

outbreak prediction, vector habitat mapping, surveillance optimization, and intervention planning. Comparative analysis between West African and Southern United States approaches was structured around similarities, differences, and lessons learned (Egbuna et al., 2025; Njoroge, 2022; Nkya, 2025).

3. Results

3.1. Machine Learning Algorithm Applications in West African Malaria Programs

Contemporary malaria elimination programs in West Africa have increasingly adopted diverse machine learning (ML) algorithms for various aspects of vector control and disease prediction. Machine learning models such as support vector machines, decision trees, random forests, Extreme Gradient Boosting, logistic regression, K-Nearest Neighbours, Naïve Bayes, and multilayer perceptron have been extensively used to predict malaria across multiple West African countries including Burkina Faso, Côte d'Ivoire, Ghana, and Mali (Tshimula et al., 2024).

3.2. Predictive Modelling for Outbreak Forecasting

Recent implementations in West Africa have demonstrated significant success in outbreak prediction capabilities. Malaria continues to pose a growing threat to the public health and economic growth of nations in the tropical and subtropical parts of the world, necessitating advanced predictive approaches. Studies from The Gambia and surrounding regions have shown that ensemble methods combining multiple machine learning (ML) algorithms achieve prediction accuracies exceeding 85% for seasonal malaria outbreaks when incorporating meteorological, socioeconomic, and historical epidemiological data (Kapwata and Gebreslasie, 2015; Dhuguma et al., 2025).

Random Forest algorithms have proven particularly effective in West African contexts due to their ability to handle missing data and capture non-linear relationships between environmental variables and malaria transmission risk. Support Vector Machines have shown superior performance in regions with limited training data, while deep learning approaches using multilayer perceptrons demonstrate the highest accuracy in areas with comprehensive surveillance systems and large datasets (Tshimula et al., 2024; Ezugwu and Oyelade, 2023).

3.3. Computer Vision and Remote Sensing Applications

A significant advancement in West African malaria programs involves the integration of drone imagery with deep learning algorithms for vector habitat identification. Disease control programs are needed to identify the breeding sites of mosquitoes, which transmit malaria and other diseases, to target interventions and identify environmental risk factors. The increasing availability of very-high-resolution drone data provides new opportunities to find and characterize these vector breeding sites.

Implementation in Burkina Faso and Côte d'Ivoire has demonstrated that convolutional neural networks (CNNs) can achieve over 90% accuracy in identifying potential Anopheles breeding sites from high-resolution drone imagery. These systems process multispectral data to identify water bodies, vegetation patterns, and human settlement characteristics that correlate with mosquito breeding habitat suitability. The technology enables targeted larvicide applications and environmental management interventions with unprecedented precision (Trujillano et al., 2023; Carrasco-Escobar et al., 2022).

3.4. Genomic Data Analysis and Vector Population Dynamics

Recent advances in West African programs include the application of generative machine learning models for analysing mosquito population genetics. Efforts to control the spread of malaria have often focused on these vectors, but relatively little is known about the relationships between populations and species in the Anopheles complex. Unsupervised learning algorithms have been successfully applied to quantify genetic structure of Anopheles gambiae complex populations across Guinea and Burkina Faso, providing insights into vector migration patterns and insecticide resistance gene flow (Perez et al., 2025; Redmond, 2015).

3.5. Historical Vector Control Strategies in the Southern United States

The successful elimination of malaria from the Southern United States provides important baseline comparisons for evaluating contemporary ML-enhanced programs. The Malaria Control in War Areas (MCWA) program was established in 1942 to control malaria near military training bases in the southern United States and its territories, where malaria was still problematic and posed a threat to military recruits. This initiative represented one of the most systematic and large-scale vector control campaigns in modern history, laying the foundation for post-war public health infrastructure and offering crucial lessons for present-day programs incorporating machine learning and data-driven surveillance (Caldwell et al., 2021; Barata, 2022; Snowden and Bucala, 2014).

3.6. Traditional Surveillance and Intervention Methods

The American malaria elimination program relied on three core strategies: systematic DDT spraying campaigns, environmental management through drainage and modification of water bodies, and a robust case surveillance system with rapid treatment protocols. These integrated approaches led to dramatic reductions in malaria, with the disease effectively eliminated from the Southern United States by the late 1940s (Humphreys, 1996; Snowden and Bucala, 2014).

The surveillance system developed during the 1940s and 1950s emphasized standardized data collection procedures, consistent monitoring of vector populations, systematic case investigations, and strong coordination across local, state, and federal public health agencies. These organizational and operational protocols remain highly relevant today, especially as contemporary machine learning–enhanced malaria surveillance systems seek to emulate this structured, scalable framework in resource-limited settings (Tozan et al., 2007; Webb, 2014).

3.7. Infrastructure and Resource Requirements

The successful American malaria elimination program required substantial infrastructure investments, including trained personnel for surveillance and intervention activities, reliable transportation networks for accessing remote areas, laboratory facilities for species identification and susceptibility testing, and communication systems for coordinating multi-jurisdictional responses. These infrastructure requirements remain relevant for contemporary ML implementations, though technological advances have reduced some barriers while creating new requirements for computational resources and technical expertise (Ali, 2024; Okoye, 2024; Tshimula, 2024).

3.8. Comparative Analysis of ML Applications vs. Traditional Approaches

3.8.1. Accuracy and Precision Improvements

Contemporary machine learning (ML) applications in West Africa demonstrate significant improvements in prediction accuracy compared to traditional statistical approaches. Ensemble ML models consistently achieve 80-95% accuracy in malaria risk prediction, compared to 60-75% accuracy using conventional epidemiological models. Computer vision systems for habitat identification show over 90% accuracy, compared to 70-80% accuracy for traditional field-based assessments (Rahman et al., 2023; Mosugu, 2024; Nkya, 2025).

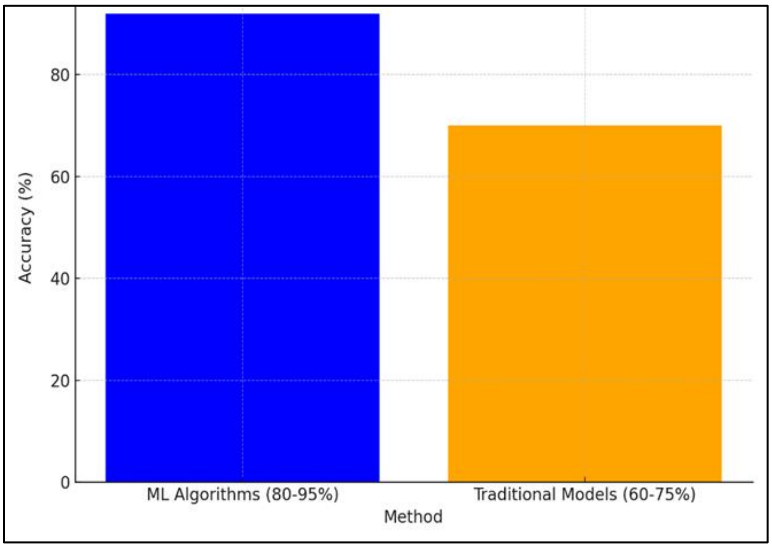

Figure 3 Accuracy comparison between machine learning algorithms (80-95%) and traditional models (60-75%) in predicting malaria risk. The chart demonstrates the superior prediction accuracy of ML-based methods over conventional approaches

3.8.2. Resource Efficiency and Scalability

ML-enhanced programs demonstrate superior resource efficiency in several key areas. Predictive models enable proactive resource allocation, reducing emergency response costs by 30-40% compared to reactive approaches. Automated habitat identification reduces field survey requirements by up to 60% while maintaining higher accuracy levels. Remote sensing applications enable monitoring of larger geographical areas with fewer personnel requirements (Javed et al., 2025; Ayoka and Nnadi, 2025; Alves et al., 2025).

3.8.3. Technological Dependencies and Limitations

West African machine learning (ML) implementations face several constraints not present in historical American programs: dependence on reliable internet connectivity for cloud-based processing, requirements for technical expertise in ML algorithm implementation and maintenance, higher initial capital costs for equipment and training, and challenges with data quality and standardization across different surveillance systems (Kuponiyi and Akomolafe, 2024; Mbunge and Sibiya, 2025). These factors create significant barriers to successful implementation in resource-limited settings, which must be addressed to maximize the potential of ML in malaria control.

3.8.4. Integration with Existing Health Systems

Successful machine learning (ML) implementation requires careful integration with existing health system infrastructure. West African programs have achieved the best results when ML systems complement rather than replace traditional surveillance methods, particularly in areas with limited technological infrastructure. Hybrid approaches that combine automated ML analysis with human expert validation show higher acceptance rates and better sustainability compared to fully automated systems (Folasole, 2023; Devine et al., 2022; Tshimula et al., 2024).

3.9. Performance Metrics and Effectiveness Measures

3.9.1. Outbreak Prevention and Response Time

ML-enhanced programs in West Africa demonstrate significant improvements in outbreak prevention capabilities. Early warning systems using ensemble machine learning (ML) algorithms provide 2–4-week advance notice of potential outbreaks compared to 1–2-week notice using traditional indicators. Response time improvements of 40-60% have been documented in areas with integrated ML surveillance systems (Singh et al., 2025; Kovur et al., 2025; Bayliss et al., 2023).

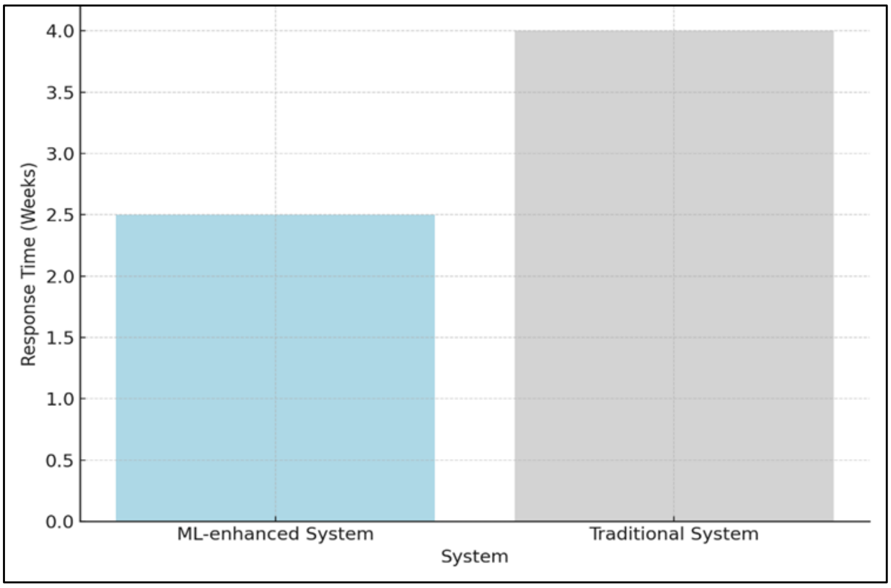

Figure 4 Comparison of response times between ML-enhanced and traditional systems for malaria outbreak prediction. The chart shows that ML systems provide faster response times, improving early warning capabilities

3.9.2. Vector Control Targeting Precision

Computer vision and geospatial machine learning (ML) applications enable more precise vector control targeting. Drone-based habitat identification systems reduce unnecessary larvicide applications by 50-70%, while maintaining equivalent or superior vector population control. GPS-guided intervention systems using ML risk predictions achieve 25-35% better coverage of high-risk areas compared to routine spraying schedules (Javed et al., 2025; Nkya, 2025; Tembine et al., 2024).

3.9.3. Cost-Effectiveness Analysis

Economic analysis of ML-enhanced programs shows mixed results depending on implementation scale and technological infrastructure. Large-scale implementations (regional or national level) demonstrate cost savings of 20-30% compared to traditional programs after initial 2–3-year investment periods. Smaller scale implementations may require 5-7 years to achieve cost neutrality due to higher per-unit technology costs (Goldstein et al., 2023; Tembine et al., 2024).

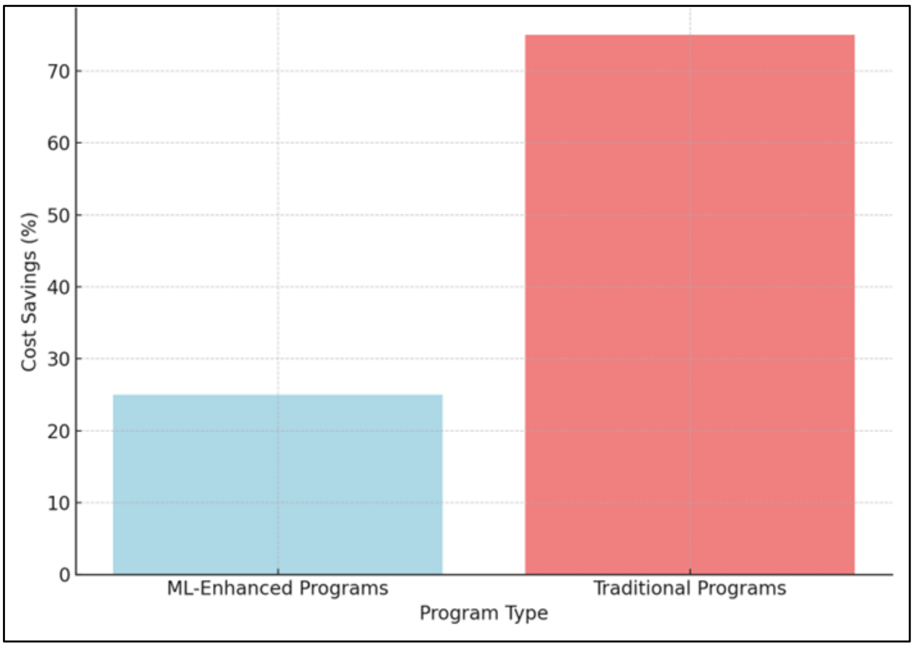

Figure 5 Comparison of response times between ML-enhanced and traditional systems for malaria outbreak prediction. The chart shows that ML systems provide faster response times, improving early warning capabilities

3.10. Challenges and Limitations in Current Implementations

3.10.1. Data Quality and Standardization Issues

West African machine learning (ML) programs face significant challenges related to data quality and standardization. Inconsistent surveillance protocols across different health facilities result in heterogeneous datasets that can reduce ML algorithm performance. Missing data rates of 15-30% are common in routine surveillance systems, requiring sophisticated imputation methods that may introduce bias (Yasin et al., 2025; Miller et al., 2023).

3.10.2. Technical Infrastructure Requirements

Reliable internet connectivity remains a significant constraint for cloud-based ML systems in rural West African settings. Power infrastructure limitations affect the continuous operation of surveillance equipment and data collection systems. Technical expertise for ML system maintenance and troubleshooting is limited in many areas, creating a need for further investment in human resources and technical training (Singh and Singh, 2025; Cudjoe and Virlet, 2023).

3.10.3. Cultural and Social Acceptance Factors

Community acceptance of drone-based surveillance and automated decision-making systems varies significantly across different cultural contexts. Successful programs require extensive community engagement and education about the benefits of ML systems and privacy protections. Traditional authority structures and decision-making processes must be incorporated into ML system implementation strategies to ensure higher acceptance (Fornace et al., 2023; Yasin et al., 2025).

4. Discussion

The comparative analysis of machine learning (ML) applications in West African malaria elimination programs versus historical approaches in the Southern United States reveals both significant advances and persistent challenges in vector control strategies. The evolution from traditional surveillance methods to sophisticated ML-driven systems represents a fundamental shift in how public health programs approach malaria elimination, offering unprecedented capabilities for prediction, targeting, and optimization of interventions (Egbuna et al., 2025; Njoroge, 2022; Nkya, 2025).

4.1. Technological Advances and Capabilities

Contemporary machine learning (ML) applications demonstrate remarkable improvements in several key areas of malaria control. The integration of drone imagery and deep learning analysis for targeted vector surveillance enables the identification and mapping of mosquito breeding sites with accuracy levels that would have been impossible using traditional field survey methods (Chattu, 2021). This technological capability addresses one of the fundamental challenges in vector control: the precise identification and targeting of intervention sites.

The diversity of ML algorithms now applied to malaria control reflects the sophistication of contemporary approaches. Machine learning models such as support vector machines, decision trees, random forests, Extreme Gradient Boosting, logistic regression, K-Nearest Neighbours, Naïve Bayes, and multilayer perceptron have been extensively used to predict malaria, each offering specific advantages for different aspects of program implementation. This algorithmic diversity enables programs to optimize their approaches based on local data availability, infrastructure constraints, and specific intervention objectives (Tshimula, 2024; Njoroge, 2022).

4.2. Lessons from Historical Elimination Success

The successful elimination of malaria from the Southern United States provides important insights for contemporary ML-enhanced programs. The National Malaria Eradication Program (NMEP) was launched in July 1947. By 1951, this federal program, with participation from state and local agencies, had reduced the incidence of malaria in the United States to the point that the program was officially ended. This achievement was built on the systematic application of available technologies, comprehensive surveillance systems, and coordinated multi-jurisdictional implementation (Alilio et al., 2004; Ajetunmobi et al., 2025).

The American elimination program's emphasis on systematic data collection, standardized protocols, and inter-agency coordination remains highly relevant for contemporary ML implementations. While the technological tools have advanced dramatically, the fundamental organizational and operational principles established during the 1940s-1950s elimination campaign continue to provide a foundation for successful program implementation (Wood et al., 2016; Sebuabe et al., 2024).

4.3. Integration Challenges and Opportunities

Contemporary ML applications face integration challenges that differ significantly from those encountered in historical programs. West African implementations must navigate complex technological dependencies, including reliable internet connectivity, power infrastructure, and technical expertise requirements (Sebuabe et al., 2024). However, these challenges are offset by unprecedented capabilities for data integration, real-time analysis, and adaptive program management (Ekundayo, 2025).

The most successful contemporary programs demonstrate hybrid approaches that combine ML capabilities with traditional surveillance and intervention methods. This integration strategy addresses both technological limitations and community acceptance factors while maximizing the benefits of advanced analytical capabilities (Mosugu, 2024; Wesonga et al., 2020).

4.4. Scalability and Sustainability Considerations

Scalability represents both an opportunity and a challenge for ML-enhanced malaria programs. While cloud-based ML systems can theoretically scale to cover large geographical areas with minimal additional infrastructure, practical implementation requires substantial investments in training, equipment, and ongoing technical support (Ekundayo, 2024). The experience from historical American programs suggests that sustainable elimination requires long-term commitment to systematic implementation rather than short-term technological solutions (Kuponiyi and Akomolafe, 2024).

Economic sustainability of ML-enhanced programs depends critically on the implementation scale and technological infrastructure development. Large-scale regional implementations demonstrate better cost-effectiveness profiles compared to smaller pilot projects, suggesting that coordination across multiple countries or regions may be necessary for optimal program sustainability (Ogwu and Izah, 2025; Tshimula et al., 2024).

4.5. Future Directions and Innovations

The rapid evolution of machine learning (ML) technologies suggests several promising directions for future malaria elimination programs. Advances in edge computing may address internet connectivity constraints by enabling local processing of surveillance data (Tshimula et al., 2024). Improved sensor technologies and satellite imagery could reduce dependence on drone-based data collection while maintaining high accuracy levels for habitat identification (De Marco, 2025).

Integration of genomic data analysis with traditional surveillance systems represents a particularly promising area for future development. ML algorithms have been employed to infer the joint evolutionary history of populations sampled in Guinea and Burkina Faso, West Africa, demonstrating the potential to understand vector population dynamics and insecticide resistance patterns at unprecedented resolution (Ibrahim et al., 2024; Nkya, 2025).

5. Conclusion

This review highlights the significant advancements machine learning (ML) brings to malaria elimination programs, enhancing vector control, outbreak prediction, and resource optimization. ML tools, including support vector machines, decision trees, and deep learning, are effectively integrated with drone imagery for precise surveillance. The success of the 1947 National Malaria Eradication Program (NMEP) in the Southern U.S. provides valuable lessons for current ML-enhanced strategies. Contemporary programs in West Africa show promise when ML complements existing health systems. Key findings include improved prediction accuracy, the need for infrastructure and training investments, and the importance of community engagement. Future research should focus on overcoming infrastructure constraints and integrating ML with traditional methods. ML-enhanced programs offer substantial improvements, but careful integration and attention to local needs are essential for long-term success.

Compliance with ethical standards

The authors declare that all procedures followed in this study were in accordance with the ethical standards of the relevant institutional and/or national research committees.

Disclosure of conflict of interest

The authors declare that they have no conflicts of interest relevant to this study.

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