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Idara JAMES [1*], *Veronica OSUBOR* [1]
[1] University of Benin, Nigeria, idara.james@physci.uniben.edu, viosubor@yahoo.com
[*] Corresponding author: idara.james@physci.uniben.edu

Machine learning evidence towards eradication of malaria burden: A scoping review

Abstract

Recent advancements have shown that shallow and deep learning models achieve impressive performance accuracies of over 97% and 98%, respectively, in providing precise evidence for malaria control and diagnosis. This effectiveness highlights the importance of these models in enhancing our understanding of malaria management, which includes critical areas such as malaria control, diagnosis and the economic evaluation of the malaria burden. By leveraging predictive systems and models, significant opportunities for eradicating malaria, empowering informed decision-making and facilitating the development of effective policies could be established. However, as the global malaria burden is approximated at 95%, there is a pressing need for its eradication to facilitate the achievement of SDG targets related to good health and well-being. This paper presents a scoping review covering the years 2018 to 2024, utilizing the PRISMA-ScR protocol, with articles retrieved from three scholarly databases: Science Direct (9%), PubMed (41%), and Google Scholar (50%). After applying the exclusion and inclusion criteria, a final list of 61 articles was extracted for review. The results reveal a decline in research on shallow machine learning techniques for malaria control, while a steady increase in deep learning approaches has been noted, particularly as the volume and dimensionality of data continue to grow. In conclusion, there is a clear need to utilize machine learning algorithms through real-time data collection, model development, and deployment for evidence-based recommendations in effective malaria control and diagnosis. Future research directions should focus on standardized methodologies to effectively investigate both shallow and deep learning models.

1. INTRODUCTION

In recent time, machine learning algorithms are expanding the frontiers of modern computing applications. Despite being a computationally intensive model that relies on complex algorithms, it provides a veritable software tool for analyses of complex problems embedded in large data (Sarker, 2021). Being a subfield of Artificial intelligence (AI) (Helm et al., 2020; Joshi, 2020), its performance is driven by the availability of voluminous but structured data for meaningful training and testing (otherwise referred to as learning process) of its model, without explicitly being programmed for the task (Lestarini et al., 2018) as obtained in the rule-based approach. The process of model learning from the intrinsic patterns associated with historical data is a characteristic feature of AI's model that possesses an inert ability to replicate human cognitive functions, such as learning and visual perception to predict the future (Qiu et al., 2016). Apart from solving complex problems involving large data, its level of preciseness, transparency, and speed increases the chances of its adoption in different areas of application.

For instance, the application of machine learning in healthcare offers remarkable opportunities to analyze daily health data to enhance patient care and timely diagnosis of disease (Mbunge & Batani, 2023; Fuhad et al., 2020). Other areas of application of machine learning are education (Tiwari, 2023), government (Chen, 2022), agriculture (Sharma et al., 2021), transportation (Li & Xu, 2021), commerce (Liu, 2022), and more. Several machine learning approaches are defined based on the characteristic nature of the available data such as: supervised, unsupervised, reinforcement learning and so on. Supervised learning utilizes labeled data and a mapping function to assign input features to the target output during predictive model training. The learning process of the trained model is subjected to test data sets (i.e. real- world data), to determine whether it can respond to classification or regression tasks accurately (Alanazi, 2022). On the contrary, unsupervised learning utilizes unlabeled data (Eckhardt et al., 2023), while semi-supervised machine learning combines labeled and unlabeled data to perform its various tasks.

Other techniques are reinforcement learning where the predictive model acts in a way to be rewarded by the environment (Verma et al., 2022), and transfer learning where the pre-trained model is incrementally trained for the desired accuracy (Ekpenyong et al., 2021). These approaches are often implemented through shallow or deep learning techniques (Lalli & Amutha, 2020). Shallow learning leverages a limited number of hidden layers in partially or fully interconnected neural networks to identify data patterns without explicit programming (Jayatilake et al., 2021). In contrast, deep learning employs multiple hidden layers of neural networks to automatically model complex non-linear relationships within the data, enhancing analytical capabilities (Jiang et al., 2018; Alnussairi & Ibrahim, 2022). However, both shallow and deep learning are studied in malaria surveillance and control, diagnoses as well as drug development (Siłka et al., 2023). The evidence(s) generated by machine learning algorithms are output of the learning models or most relevant feature(s) that is vital to decision-making and policy formulation (Gilat et al., 2024).

The workflow of machine learning process comprises the data collection phase that accepts data from single or multiple source(s) as input. The data is further processed to remove irrelevant features and select relevant ones for further analysis (Zelaya, 2019). Examples of data collection tools are: sensors, cameras, satellites, microphones, slides, scanners, thermometers and more. Thereafter, the preprocessed data is partitioned into both the training and testing sets and subjected to model learning task. During the learning wherein the training set is first utilized to train a new model followed by the test data. To test the suitability of the trained model for deployment, performance evaluation using accuracy parameters (e.g. RMSE, MAE, F1-score, Precision, Recall, ROC-AUC and more) is established to measure the validity of evidence that is generated by the model. These parameters could be further fine-tuned for improved model performance. Figure 1 shows the overall workflow of machine learning process. Typical examples of machine learning algorithms are k-nearest Neighbour (kNN), Random Forest (RF), Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Tree (DT), and more (Mahesh, 2020; Oladipupo, 2010).

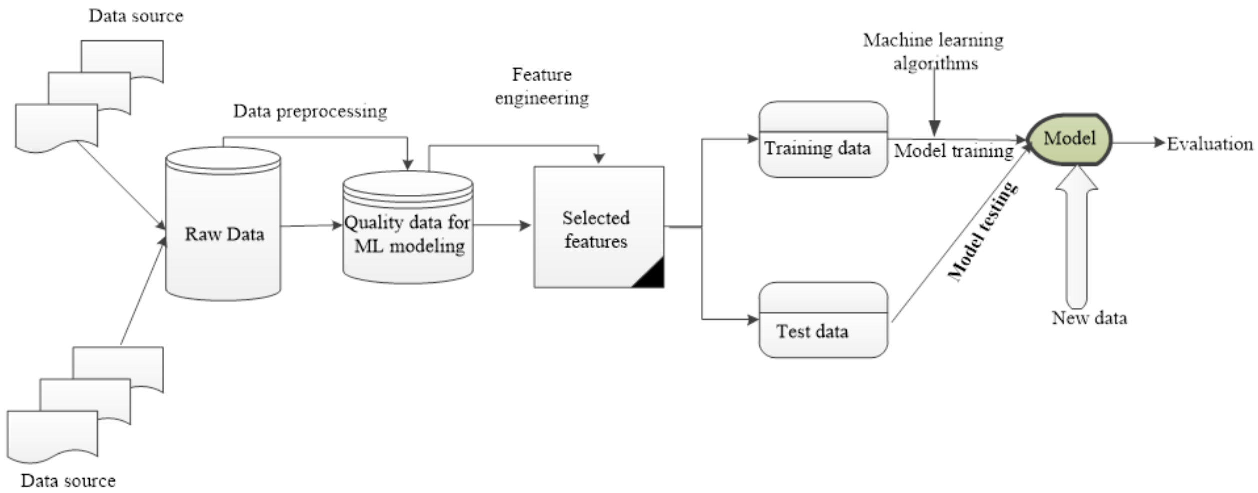
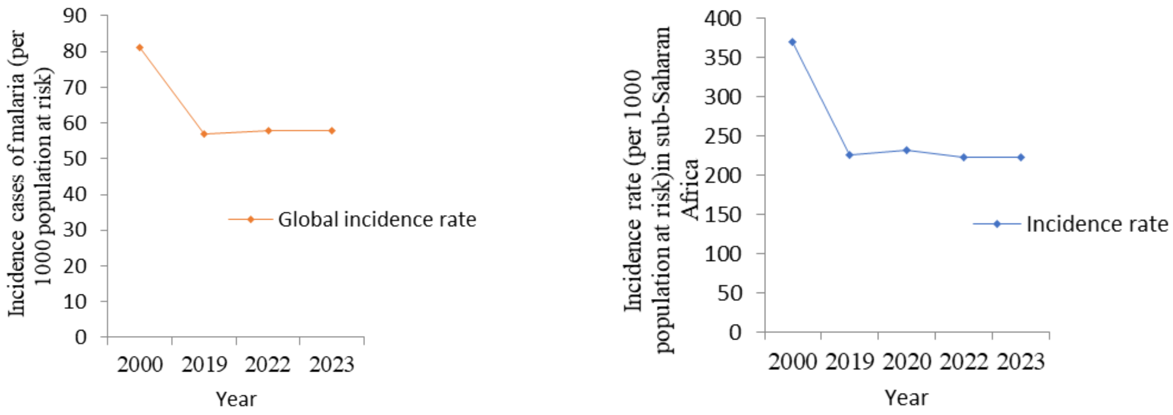


Fig. 1. Workflow of machine learning showing phases of different tasks (adapted from Singh et al., 2023)

The preference for machine learning algorithms stems from the need to gain insight into the accumulated data resulting from the advancement in the networking and communication infrastructure that supports data generation from multiple sources via collaboration technologies, e.g. Internet of Things (IoT) and geospatial technologies (Udo & Ekpenyong, 2020). Therefore, to ensure improved performance accuracy and speed in the era of big data (James & Osubor, 2023), adopting models/algorithms with proven effectiveness to explore intricate patterns inherent in the data is ideal to generate precise evidence to support decision-making and planning required for formulation of policies. However, a few studies adopt machine learning algorithms for malaria control measures, thereby hindering evidence-based recommendation to tackling the menace of malaria (Nguyen et al., 2019). Existing studies on the application of machine learning to generate evidence for the eradication of the malaria burden are available at various levels of malaria control, diagnosis, and drug development (Golumbeanu et al., 2022; Mswahili et al., 2021; Neves et al., 2020).

Malaria is one of the febrile diseases transmitted by female Anopheles mosquitoes and caused by Plasmodium parasites (Fikadu & Ashenafi, 2023). Despite being classified as an infectious disease, it is both preventable and curable (Basu & Sahi, 2017). According to the distribution of malaria incidence by the World Health Organization (Venkatesan, 2024), an estimated 249 million malaria cases were recorded globally, indicating a 5 million increase in the previous year, 2021. In 2022, approximately 223 confirmed malaria cases per 1,000 individuals at risk were reported in the sub-Saharan Africa, resulting in increased burden of the disease in the region. Notably, there was a 4% reduction in the mortality incidence rate from 2020 to 2022, indicating progress in malaria control and diagnosis via strategic health interventions in the region (Venkatesan, 2024). The graphs illustrating malaria incidence (per 1000 population at risk) between 2000 and 2023 for global and sub-Saharan African cases, are shown in Fig. 2(i) and Fig. 2(ii), respectively. Similarly, malaria mortality between 2000 and 2023 for global and sub-Saharan African cases are shown in Fig. 3(i) and Fig. 3(ii), respectively.

Specifically in Nigeria, malaria is one of the killer diseases (Kolawole et al., 2023; Oladipo et al., 2022; Ahmed et al., 2019) with annual mortality predominantly among children between the ages of 0-5 years and pregnant women. The prevalence of malaria infection across West Africa where Nigeria has the highest percentage prevalence of 27% among other countries is illustrated in Fig. 4.



(i) Global **(ii) Sub-Saharan Africa**

Fig. 2. Malaria incidence (per 1000 population at risk) between 2000 and 2023 for (i) Global and (ii) sub-Saharan Africa cases (Venkatesan, 2024)

(i) Global **(ii) Sub-Saharan Africa**

Fig. 3. Mortality of malaria between 2000 and 2023 for (i) Global and (ii) sub-Saharan Africa cases (Venkatesan, 2024)

The prevalence of increasing malaria incidence presents a huge burden on states, regions, and nations, despite interventions and programmes targeted at populace to reduce menace of malaria. This menace could be attributed to many factors among others, such as insufficient evidence to guide strategic interventions and non-adherence to sanitation standards that inhibit the rapid breeding of mosquitoes (Gooch, 2017). Others are illiteracy level among households and improper use of insecticide-treated mosquito nets, dirty source drinking water, poor roofing/floor materials, and favorable conditions for mosquitoes to thrive e.g. dirty environment filled with stagnant water and warm temperatures (Bassey & Izah, 2017; Tetteh et al., 2023).

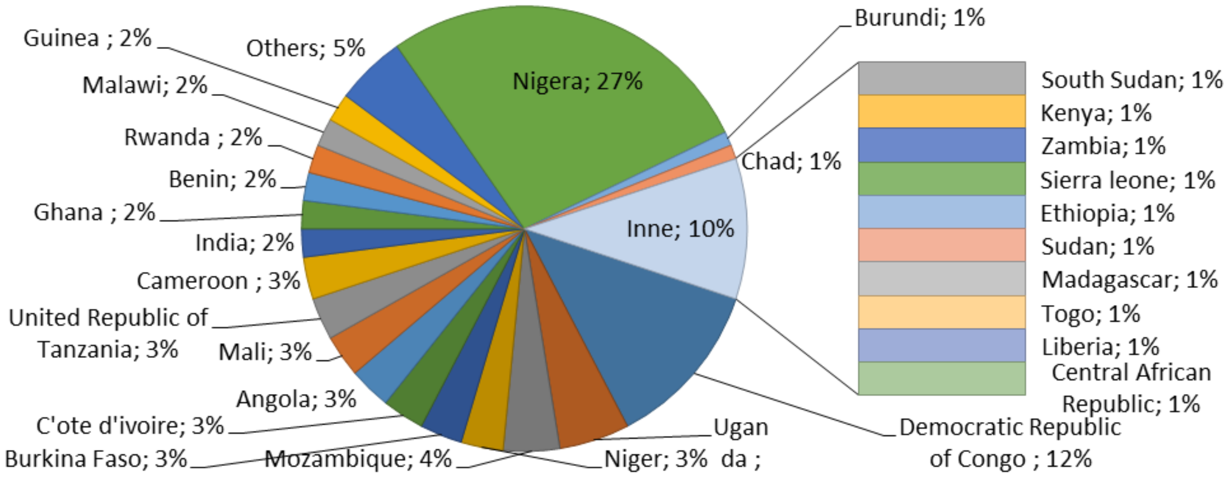


Fig. 4. Percentage of malaria prevalence in sub-Saharan Africa (Venkatesan, 2024)

Due to the availability of data on malaria incidence accumulated over the years concerning malaria vector, host and environment, there is the need to gain insights into the data to accelerate generation of evidence for malaria control and interventions for eradication of its burden (Haileselassie et al., 2023). However, existing studies on the application of machine learning in malaria are focused on the eradication of the burden through diagnosis and drug development (Ikerionwu et al., 2022; Jdey et al., 2023; Tai et al., 2022; Balerdi-Sarasola et al., 2024; Makondo et al., 2021). On the contrary, a few studies on the control of malaria focused on surveillance and estimation of malaria burden (Sarma et al., 2019; Brown et al., 2020), using statistical modeling instead of machine learning algorithms. Statistical modeling is inadequate to handle analytics involving high dimensional features with high degree of accuracy (Khan et al., 2020) I terms of the estimation of malaria burden (Taye et al., 2024; Sahu et al., 2023; Qadri et al., 2023; Deshmukh & Parag, 2023; Jahan & Alam, 2023); Kundu & Anguraj, 2023).

Therefore, based on the effectiveness of machine learning in handling complex data-driven tasks with accuracy, this scoping review seeks to identify the evidence(s) of machine learning algorithms that supports the eradication of malaria burden under the following research questions: (1) What are the strengths and weaknesses of existing statistical modeling research in supporting efforts toward the eradication of the malaria burden? (2) What types of evidence do existing machine learning studies provide in support of malaria control and diagnosis efforts, and how do these contributions align with the goal of eradicating the malaria burden? (3) How do predictive systems provide precise and actionable evidence to support the eradication of the malaria burden? To provide accurate responses to the following questions, a total of 3022 relevant articles were retrieved and reviewed from different scholarly databases such as ScienceDirect (9%), PubMed (41%), and Google Scholar (50%) as shown in Fig. 5. The remaining part of this paper is organized as follows: section 1.1 presents the introduction. Section 2.1 describes the method and the results are presented in section 3.1. This section is followed by a discussion in section 4.1 and conclusion in section 5.1.

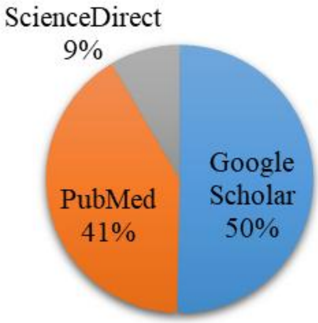


Fig. 5. Percentage distribution of retrieved articles from the scholarly databases, namely: Science Direct, PubMed and Google Scholar

This review aims to evaluate the literature on the application of different approaches of machine learning algorithms towards generating precise evidence for eradication of malaria burden. Our approach to review is defined under the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) (Lukwa et al., 2024) guidelines as follows: definition of research questions, search for articles, filtering of articles, data extraction and synthesizing of results.

2. SCOPE OF THE REVIEW

The reviewed studies primarily concentrate on the diagnosis and control of malaria. Additionally, studies related to malaria surveillance and prevention is included within the broader context of malaria control in this analysis. For example, to comprehend the application of shallow and deep learning in malaria control studies, Comert et al. (2020) highlight the importance of detecting outbreaks. Additionally, other research efforts have investigated the prediction of such outbreaks through the examination of meteorological and climatic data (Singh et al., 2023; Stephen et al., 2021; Martineau et al., 2022). Moreover, Harvey et al. (2021) discuss the early prediction of malaria risk and identify other significant contributing factors in their studies.

2.1. Search for relevant articles

To overcome the challenge of retrieval of irrelevant articles in the subject area of Computer Science query terms are selected and formulated as logical search strings depicted as Q1, Q2, Q3, Q4, Q5. After the initial search in the subject area of Computer Science, voluminous articles were retrieved resulting in 3022 articles. However, the final searches were streamlined to articles published between 2018 - 2024 in Science Direct, PubMed, and Google Scholar. The logical search strings used for the retrieval of articles are as follows:

Q1: Machine learning AND malaria burden estimation
Q2: Machine learning AND malaria diagnosis
Q3: Machine learning AND malaria predictions
Q4: Machine learning AND malaria prevention AND control
Q5: Machine learning AND cost burden of malaria

These search strings aim to enhance the relevance of the search results to the topic at hand. It also facilitates a more focused inquiry and captures the interactions between key concepts. This constructive approach streamlines the research process, ensuring the findings are both relevant and efficient in addressing the specific area of interest in the research.

The retrieved articles from the respective scholarly databases were subjected to identification, screening, eligibility and inclusion phases of the PRISMA-ScR protocol as illustrated in Fig. 6.

2.2. Article selection and filtering

Based on exclusion and inclusion criteria, a total of 2963 and 61 articles were excluded and included, respectively in the final list of articles for the review. These included articles were also independently filtered by machine learning researchers. The exclusion and inclusion criteria considered are outlined as follows.

2.3. Exclusion criteria

The exclusion criteria considered in this review paper are as follows: Articles not published in English, Articles published in book chapters, encyclopedias, review papers, and conference abstracts

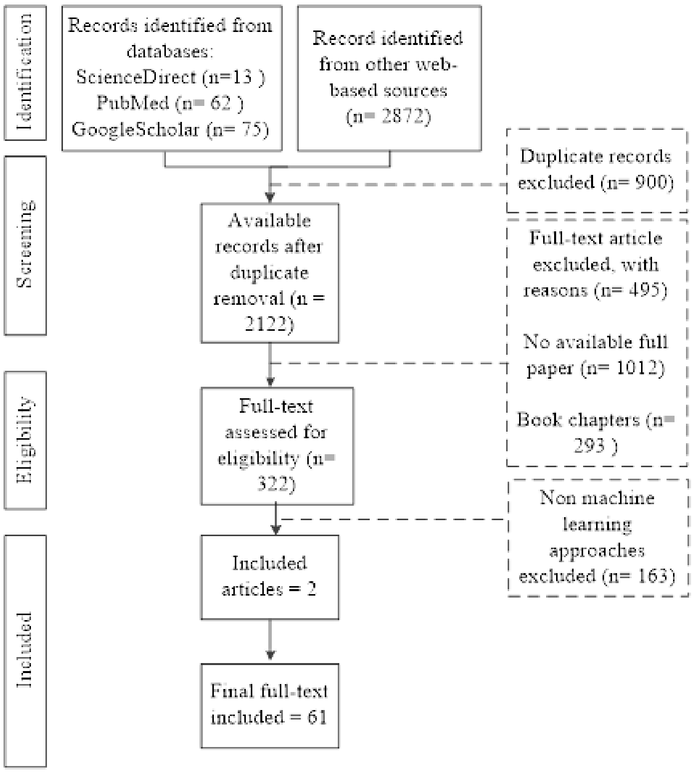


Fig. 6. PRISMA-ScR protocol showing Identification, Screening, Eligibility, and Included phases of retrieved articles on the machine learning evidence towards eradication of malaria burden

2.4. Inclusion criteria

This paper covers the following articles: Research articles published between 2018-2024 inclusively including journals and conference papers indexed by IEEE related to the subject area of Computer Science. In all, a total of 61 articles were finally considered as the final full-text included in the review.

2.4.1. Extraction of features from the retrieved data

To provide answers to the research questions, relevant features of the articles were extracted and summarized for this study. The features of the articles reviewed, labeled A1, A2, …, A6, were analyzed to address the research questions and summarized in Tables 3 to 6.

A1: Objective of the study
A2: Source of data
A3: Algorithm(s) defined in the methodology
A4: Evaluation parameter
A5: Machine learning (i.e. shallow or deep learning approach)
A6: Significance of study in terms eradication of malaria burden.

2.5. Results

Distribution of Statistical Modeling and Machine Learning (either Shallow of Deep Learning) Articles towards Generation of Precise Evidence for Eradication of Malaria Burden.

From the number of relevant articles selected for review in the subject area of Computer Science on the application of machine learning towards evidence generation for eradication of malaria burden as shown in the PRISMA-ScR in Fig. 6, it is observed that statistical modeling and shallow machine learning approaches are often used in the malaria control studies with a few related works using deep learning approach. This trend poses a setback to the generation of precise evidence and also presents research gaps confronting the malaria burden at the early stage of prevention and control through real-time surveillance with a high-performance machine learning approach. However, there is a notable increase in transiting from shallow to deep learning research approaches in malaria diagnosis, which could lead to improved accuracy (Hoyos & Hoyos, 2024). Similarly, as the number of researches in malaria control increases, there is a corresponding minimal increase in the malaria diagnosis research in the cases of statistical modeling and shallow machine learning.

On the contrary, a decrease in the number of research articles on malaria control could be attributed to the prevalence of higher malaria burden due to inadequate evidence to support malaria control measures using machine learning. Whereas the increase in the number of research articles on malaria diagnosis could be attributed to improved health outcomes in disease diagnosis. Therefore, the research gap posed by the inadequacy of precise evidence could be bridged with the application of modern research techniques using shallow or deep learning to generate precise evidence that would guide decision-making and policy formulation towards the eradication of malaria burden in terms of control and prevention (Adegbite, 2023). The number of research articles using either shallow or deep learning for provision of evidence in malaria control and diagnosis is shown in Fig. 7.

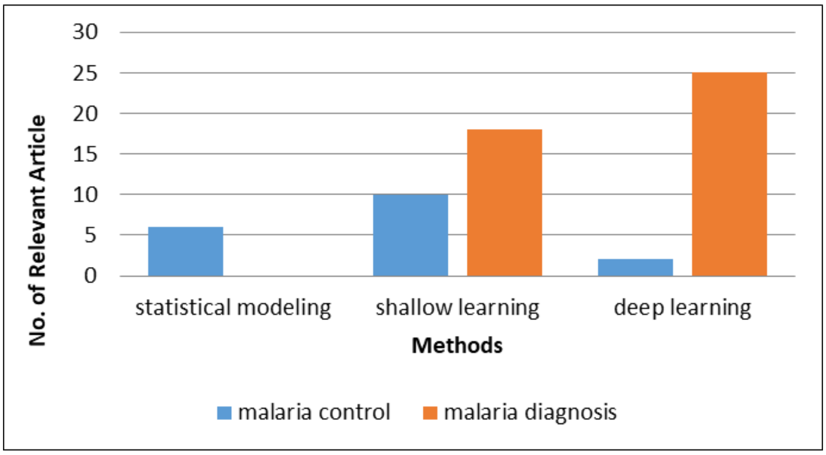


Fig. 7. Distribution of the number of reviewed articles involving statistical modeling, shallow and deep learning towards eradication of malaria burden in terms of control and diagnosis

The annual distribution of published articles focusing on malaria control and diagnosis, leveraging both shallow and deep machine learning techniques, is illustrated in Fig. 8. The data indicate a notable increase in researchers' interest in adopting deep learning approaches from 2018 to 2024. In contrast, there has been a decline in the application of shallow machine learning models and algorithms throughout the same period. This transition from shallow to deep learning could be attributed to the growing demand for precise evidence in the effort to eradicate the malaria burden, particularly as the volume and complexity of available data have increased in recent years.

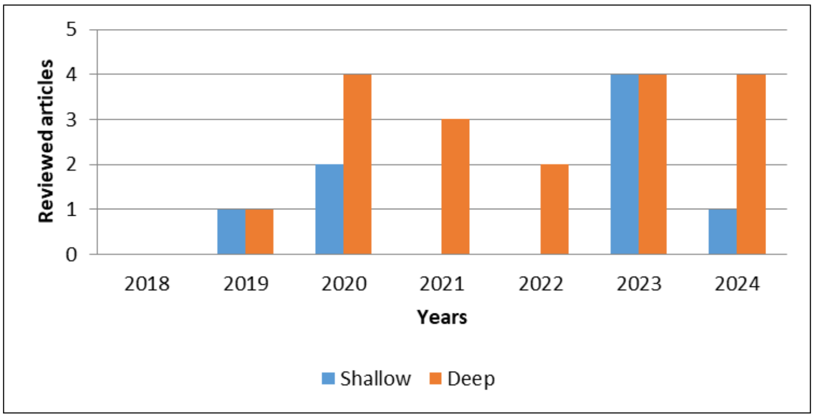


Fig. 8. Yearly distribution of reviewed articles involving malaria control and diagnosis using shallow and deep machine learning models/ algorithms

Distribution of the Reviewed Articles on Application of Machine Learning for Malaria Control and Diagnosis

An analysis of the reviewed articles reveals a significant increase in the number of publications on shallow and deep learning applications for malaria diagnosis in 2023. Based on this trend, it is expected the number of these articles will likely surpass that of previous years at the end of 2024. Figure 9 illustrates the trend of researches using shallow and deep learning in malaria diagnosis and control. From the graph in Fig. 9, it is evident that shallow and deep learning are mostly applied in the diagnosis rather than malaria control where voluminous data characterized with high-dimensional features is associated with clinical data. However, the volumes of data generated during malaria surveillance in the era of Internet of Things (IoT) technology require a solution approach capable of handling large data sets with speed and accuracy (Ayalew et al., 2024). Therefore, adoption of machine learning approach to provide evidence for malaria control can lead to strategic planning and optimal resource allocation for the heavily burdened households.

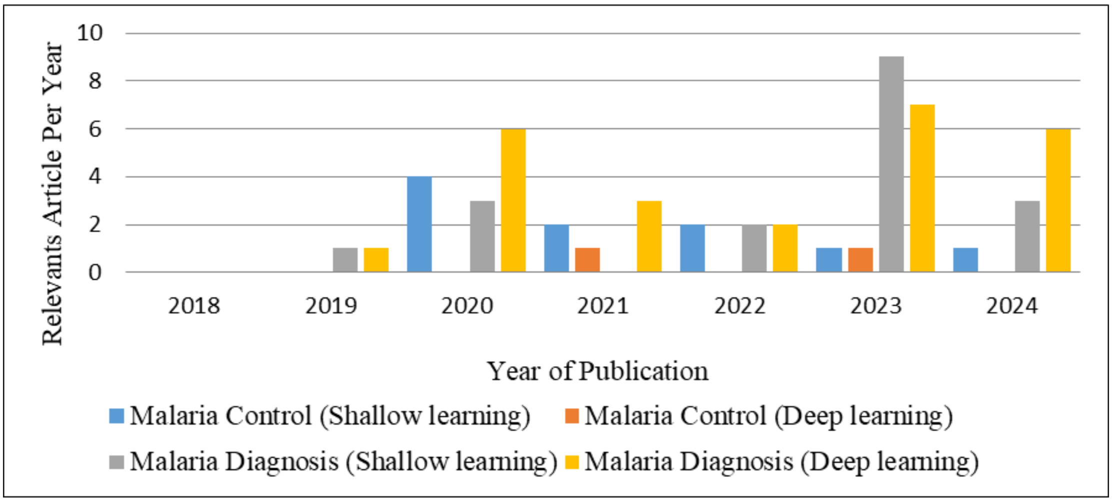


Fig. 9. Distribution of the number of reviewed articles on application of machine learning for malaria control and diagnosis

From the summary of the application of machine learning algorithms in the eradication of malaria burden, it is also observed that evidence generated from the core machine learning task is focused on the eradication of burden in terms of diagnosis, with a few studies on the control of malaria using either shallow or deep learning approach. The dearth of literature on malaria control in recent studies is synonymous with high malaria burden on households despite several interventions to address the menace. The availability of precise knowledge control can minimize the disease burden, support informed decision-making, and policy formulation to guide strategic interventions and planning (Bent et al., 2018; Awine et al., 2017). However, statistical modeling approaches estimated the impact and quantified malaria burden on households using regression analysis with single value output. This value provides an estimate of malaria burden in terms of high or low burden. One of the strengths of this model is its transparency, which effectively identifies key predictors and clarifies how each variable influences the outcome. This clarity not only enhances the model's interpretability but also empowers stakeholders to understand the intricate relationships among variables, ultimately leading to more informed and strategic decision-making. Apart from the inability of the model to perform multiclass classification, generalization of solutions with new sets of real-world data with high dimensionality (Conlin, 2024) presents a research gap that machine learning can address with accuracy.

The summary of the reviewed statistical modeling approaches towards the eradication of malaria burden is shown in Table 1. The categories of features from malaria indicator and demographic health surveys data (Affiah et al., 2022) used with the statistical modeling in Table 1 to estimate malaria burden is presented in Table 2. These categories of features include community, household, and socio-economic features. Other features are sociodemographic features, behavioural risk, treatment and women features.

Tab. 1. Summary of existing application of statistical modeling in eradication of malaria burden in terms of control

Ref	Objective	Data source	Methodology	Strength	Significance
(Affiah et al., 2022)	Estimate malaria burden	Household Survey	Multivariate logistic regression model using direct and indirect cost data.	Classification and single valued output	Malaria control
(Ayogu et al., 2021)	Estimate malaria burden	Survey data from patient folder	Descriptive statistical model using direct medical cost	Classification and single valued output	Malaria control
(Tafera et al., 2020)	Estimate malaria burden	Household Survey	Multivariate logistic regression analysis using economic and associated data features.	Classification and single valued output	Malaria control
(Paudel & Pant, 2020)	Estimate malaria burden	Household Survey	Ingredient-based approach using probit regression model	Classification and single valued output	Malaria control
(Singh et al., 2019)	Estimate malaria burden	Household Survey	Human capital method (i.e. Linear model)	Classification and single valued output	Malaria control
(Dalaba, et al., 2018)	Estimate malaria burden	Household survey	Quantitative statistical design using t-test using care seeking and cost of treatment data for under-five years children in Ghana.	Classification and single valued output.	Malaria control

Tab. 2. Existing studies on categories of features used from malaria indicator and demographic health surveys data to estimate the burden of malaria

Category	Example of features covered	Reference
Geolocation (or community) features)	Region, Types of places of residence	(Patrick et al., 2023; Deressa et al., 2023)
Household features	Source of drinking water, Main floor material, Main roof material, Type of toilet facility, Household has electricity, Toilet facility shared with other households, Type of cooking fuel	(Yang et al., 2019; Woolley et al., 2022; García et al., 2023)
Socio-economic features	Educational attainment, Husband/partner's occupation, Husband/partner worked in last 7 days/12 months, Respondent currently working. Literacy, Wealth index combined	(Anjorin et al., 2023; Degarege et al., 2019; Sharma et al., 2021; Tefera et al., 2020)
Socio-demographic (or individual) features	Number of households members, Number of children under 5 years, Sex of head of household, Age of head of household, Age of child in month, Child sex, Ideal number of children, Educational attainment, Husband/partner's occupation, Husband/partner worked in last 7 days/12 months, Current work status of household member/head, Respondent currently working, Relationship of head of household with members.	(Awosolu et al., 2021; Tefera et al., 2020; Ojurongbe et al., 2023)
Behavioural risk features	Has mosquito bed net for sleeping, Availability of Children under 5 years who slept under, mosquito bed net last night (DHS questionnaire), Number of mosquito bed nets, Number of children who slept under mosquito bed net previous night Type of mosquito bed net(s) used last night.	(Finda et al., 2019; Bhatt et al., 2015; Patrick et al., 2023)
Malaria treatment features	Cost of treatment for fever (in Naira), Final result of malaria from blood smear test, Result of malaria rapid test, Status of fever in last two weeks, Treatment for fever in last two weeks, Was Child tested for malaria?, Number of days after fever began treatment /advice was sought, Place where first treatment was sought.	(Oyewola et al., 2022; Apeagyei et al., 2024; Peprah et al., 2024)
Women features	Currently pregnant? Duration of current pregnancy in months.	(Fana et al., 2015; Chijioke-Nwauche et al., 2020)

2.6. Research questions

1. What are the strengths and weaknesses of existing statistical modeling research in supporting efforts toward the eradication of the malaria burden?

To quantify the malaria burden on households, a few existing studies adopted regression analysis to estimate the burden of malaria (Eze & Asogwa, 2021). Out of the total of eight articles reviewed as shown in Table 1, 87.5% of the reviewed articles adopted regression models to analyze household survey data aimed at estimating malaria burden on households, while 12.5% combined the generalized linear model and machine learning to generate evidence as a multiclass classification task (Jahan & Alam, 2023; Diker, 2022; Brown et al., 2020). The multivariate regression (Affiah et al., 2022, Tefera et al., 2020), quantitative and descriptive statistical modeling (Dalaba, et al., 2018; Ayogu et al., 2021) as well as linear model (Paudel & Pant, 2020) produce the result as a single value weighed as binary classification output in terms of predicting either high or low malaria burden on households. Although the output generated by the statistical modeling remains valid evidence to guide decision-making and planning (Treskova, 2020), it lacks the preciseness required for strategic prevention and control of malaria in real-time (Hemingway et al., 2016).

Additionally, the inherent inability of the regression models to generalize solutions given real-world data as well as the superimposition of predefined model(s) on the available data often leads to model bias and over-fitting (Hastings et al., 2020).

2. What types of evidence do existing machine learning studies provide in support of malaria control and diagnosis efforts, and how do these contributions align with the goal of eradicating the malaria burden?

The evidence(s) provided by the existing application of machine learning algorithms towards the eradication of malaria burden is focused on the use of both shallow and deep learning approaches (Mbunge et al., 2023). A summary of existing studies on the application of machine learning models used in the eradication of malaria burden in terms of control and diagnosis is presented in Table 3. In Hoyos and Hoyos (2024), Liu et al. (2023), studied deep learning with Yolov8, Yolov5and CNN, respectively using blood smear images to detect the number of plasmodium parasite and leukocytes to provide a model for malaria diagnosis. Other deep learning tasks involving malaria diagnosis were studied to support analysis of parasitized and uninfected red blood cells (Maturana et al., 2023), forecast malaria impact on population using CNN (Hemachandran et al., 2023), perform malaria diagnosis with CNN (Loddo et al., 2022; Onuche-Ojo et al., 2024). The performance of the evidence generated by the developed deep learning model is evaluated with parameters such as accuracy, sensitivity, specificity, Area under Curve- Receiver Operating Characteristics, precision, recall, and so on.

Similarly, shallow learning tasks used in malaria diagnosis are studied in terms of the classification of malaria-related data types (Barraclough et al., 2024; Okagbue et al., 2020), analysis of patient's malaria data (Bilal, 2023; Qadri et al., 2023), misdiagnosis (Okagbue et al., 2020).

Tab. 3. Summary of existing studies on application of machine learning models in eradication of malaria burden in terms of diagnosis

Ref	Objective	Data source	Algorithm	Parameter	Approach	Significance
(Hoyos & Hoyos, 2024)	Detect and count parasites along with leukocytes	Thick blood smear images from Makerere AI Lab, Uganda	Yolov8	Accuracy Sensitivity Specificity mAP	Deep	Malaria diagnosis
(Barraclough et al., 2024)	Classify malaria types	Patient file Survey	NB, RF, Meta Bagging, and Voting	ACC, TP, FP, Precision, Recall, F-Measure,	Shallow	Malaria diagnosis
				AUC-ROC, speed and Confusion Matrix		
(Bilal, 2023)	Analyze patients' malaria data	Kaggle	J48 Tree, Naive Bayes, SVM, KNN, and Logistic Regression	AUC and accuracy	Shallow	Malaria diagnosis

Tab. 3. Summary of existing studies on application of machine learning models in eradication of malaria burden in terms of diagnosis, continuation

Ref	Objective	Data source	Algorithm	Parameter	Approach	Significance
(Qadri et al., 2023)	Analyze malaria images of Parasitized and uninfected red blood cells	NIH Malaria Dataset	(NASNet and NNR	Accuracy, Target class, Precision, Recall F1	Shallow	Malaria diagnosis
(Okagbue et al., 2020)	Misdiagnosis	Peered reviewed data article	Adaptive boosting algorithms	Accuracy, precision, error rate	Shallow	Malaria diagnosis
(Shi et al., 2020)	Classify plasmodium blood smear images	Malaria images from Central South Hospital of Wuhan University, China	Ensemble neural network	Accuracy	Shallow	Malaria diagnosis
(Maturana et al., 2023)	Analyze malaria images of parasitized and uninfected red blood cells	Thick blood smear images from Samsung Galaxy S20 smartphone camera	YOLOv5x, Faster R-CNN, SSD, and RetinaNet object detection neural networks	precision, recall, F-score, and mAP	Deep	Malaria diagnosis
(Hemachandran et al., 2023)	Forecast malaria impact on population over time	Parasitized cell images/infected cell images from National Institutes of Health (NIH)	CNN, MobileNetV2, and ResNet50	training and testing loss, precision, recall, Fi-score, and ROC curve	Deep	Malaria control
(Liu et al., 2023)	Rapid detection of malaria parasites.	mSmartMalariaNET	YOLOv5 model, AAM and CNN	Acc. Precision, Sensitivity, Specificity, F1-Score, Auc	Deep	Malaria diagnosis
(Chakradeo et al., 2021)	Model low cost malaria diagnosis with overall accuracy	images of Giemsa-stained thin blood smear slides from Chittagong Medical College Hospital, Bangladesh	VGG-based model	accuracy, precision, recall, and F1-score, specificity	Deep	Malaria diagnosis
(Tuba et al., 2020)	Diagnosis malaria	Parasitized cell images/infected cell images from National Institutes of Health (NIH)	CNN	Accuracy, precision, recall, and F1-score.	Deep	Malaria diagnosis
(Onuche-Ojo et al., 2024)	Web-based diagnostic tool	Parasitized cell images/infected cell images from Kaggle repository	CNN and TensorFlow model	Precision, recall, F1-score	Deep	Malaria diagnosis

HMIS = Health Management Information System, NIH = National Institutes of Health, C5.0 = specific decision tree algorithm, ANN = Artificial Neural Network, k-NN = K-nearest Neighbor, LR = Linear Regression, AUC-ROC = Area Under Curve-Receivers operating Characteristics, GaussianNB = Gaussian Naive Bayes, RF = Random Forest, RMSE = Root mean Square Error, MAE = Mean Absolute Error, MSE = Mean Squared Error, OneR = One Rule, ZeroR = zero Rule, NN = Neural Network, GRNN = Generalized Regression Neural Network, GPR = Gaussian Process Regression, SVR = Support Vector Regression, RBNN = Radial Basis Neural Networks, PSO = Particle Swarm Optimization, MLP = Multilayer perceptron, GB = Gradient boosting, GP = Gaussian process, GNB = Gaussian naïve bayes, LDA = linear discriminant analysis, RFR = Random Forest Repressors, EXGBoost = Extreme Gradient Boost, GLM = Generalized Linear Model, PCC = Pearson Correlation Coefficient.

3. How do predictive systems provide precise and actionable evidence to support the eradication of the malaria burden?

Advancement in computational resources (in terms of hardware, software, and availability of large volumes of data) has necessitated the development of computationally intensive data-driven solutions in predictive malaria models or systems. The implementations of these models are performed with regression, shallow, and deep machine learning (Khan et al., 2024; Ojurongbe et al., 2023; Singh et al., 2023). While regression models are formulated to provide a single-valued output which is used to obtain the estimates of malaria burden, shallow and deep learning models are built to predict malaria burden in terms of multiple values to support multi-class classification, making its predictions more precise. However, the output of the learning model differs based on the type of data in use. In recent times, precise evidence is in high demand to support informed decision-making and improve health outcomes and personalized care (Christopoulo, 2024).

In malaria control, evidence(s) are generated as the output of classification/ prediction models/ systems of shallow machine learning using meteorological data (Taconet et al., 2021), a combination of meteorological and clinical/ incidence data (Akinbobola & Omotosho, 2013). Similarly, in malaria diagnosis, evidence is generated from the output of shallow or deep machine learning using clinical data (Lee et al., 2021; Yadav et al., 2021). Other research to eradicate the malaria burden in terms of detection of malaria parasites using shallow machine learning (Taye et al., 2024; Ahmad et al., 2023; Babikir & Thron, 2022; Gezahegn et al., 2018), prediction of the outbreak (Komugabe et al., 2024; Mbunge et al., 2023), and risk of malaria (Sahu et al., 2023; Onyijen et al., 2023; Khoirunnisa & Ramadhan, 2023; Jimoh et al., 2022), and interpretation of the output of malaria prediction (Rajab et al., 2023; Afolabi et al., 2023; Mohapatra et al., 2020). Table 4 shows the summary of evidence(s) from predictive malaria models/or systems towards the eradication of the malaria burden.

Tab. 4. Summary of existing studies on application of machine learning in eradication of malaria burden using predictive models

Ref	Objective	Data source	Algorithm	Parameter	Approach	Significance
(Khan et al., 2024)	Prediction model of malaria outbreaks	Historical meteorological and clinical dataset from HMIS	C5.0 DT, ANN, k-NN,SVM with linear and radial kernels, LR, XGBoost, and RF	Accuracy, sensitivity, specificity, AUC-ROC	Shallow	Malaria control
(Sahu et al., 2023)	Prediction model of malaria risk	Demographic /clinical date from Patient records	LR, DT classifiers, gaussianNB, RF, and extratree classifiers	Precision, Recall, F1-Score	Shallow	Malaria diagnosis
(Onyijen et al., 2023)	Prediction model of malaria risk	Demographic /clinical date from Kaggle repository	Supervised machine learning techniques	RMSE, MAE, MSE, F1-score	Shallow	Malaria control
(Rajab et al., 2023)	Interpret malaria prediction	-	Shapley Additive Explanation (SHAP) and Local Interpretable Model-agnostic	-	Deep	Malaria diagnosis
(Ojurongbe et al., 2023)	Predict malaria positivity	Patient data from Osogbo, Osun State, Southwest Nigeria	Penalized Regression Model, DT	Accuracy, precision(negative, positive), recall (negative, positive), F1-score (forged, real)	Shallow	Malaria diagnosis

Tab. 4. Summary of existing studies on application of machine learning in eradication of malaria burden using predictive models, continuation

Ref	Objective	Data source	Algorithm	Parameter	Approach	Significance
(Ahmad et al., 2023)	To classify data for accurate Malaria diagnosis and decision-making.	Demographic /clinical data from Patient records of Federal Medical Centre in Yola, Adamawa state.	Naïve Bayes, (J48) DT, ZeroR, and the OneR algorithm and ensemble model	Accuracy	Shallow	Malaria diagnosis
(Khoirunnisa & Ramadhan, 2023)	Detection of malaria	Secondary data from Federal Polytechnic Ilaro Medical centre, Ilaro Ogun state, Nigeria.	Bagging (Bootstrap Aggregating), DT	Accuracy	Shallow	Malaria diagnosis
(Jimoh et al., 2022)	Predict multiclass malaria infection	Hospital data and health services unit	Stacking Ensemble learning	Sensitivity, specificity, PPV, and NPV, error rate, last correct rate, last error rate, classified rate	Shallow	Malaria diagnosis
(Mariki et al., 2022)	Prediction model of malaria	Clinical data in Tanzania	supervised machine learning models	Accuracy	Shallow	Malaria diagnosis
(Singh et al., 2023)	Prediction of malaria outbreak	Meteorological data	Feed-forward NN, PSO, GRNN, GPR, SVR, RF, and RBNN	MSE, coefficient correlation, accuracy	Shallow	Malaria control
(Martineau et al., 2022)	Prediction of malaria outbreak	Climatic data	MLP, GB, Adaboost, XGboost, RF, SVM, K-nearest, GP, GNB, logistic regression, LDA, multi-model persistence	Accuracy	Shallow	Malaria control
(Harvey et al., 2021)	Predict early risk of malaria	Integrated e-Diagnostic	GP and RFR	Precision and recall	Shallow	Malaria control
(Stephen et al., 2021)	Predict malaria outbreak	Meteorological and malaria incidence data	Naive Bayes, SVM, Linear Regression, Logistic Regression, and kNN	Accuracy	Shallow	Malaria control
(Mohapatra et al., 2020)	Predict malaria outbreak	Malaria incident data	MLP, J48 classifiers	RMSE, better kappa, accuracy	Shallow	Malaria control

Tab. 4. Summary of existing studies on application of machine learning in eradication of malaria burden using predictive models, continuation

Ref	Objective	Data source	Algorithm	Parameter	Approach	Significance
(Nkiruka et al., 2020)	Classify malaria incidences	Clinical /climatic data from National Centre for Atmospheric Research (NCAR)	XGBoost, Naïve Bayes, SVM, Logistic Regression	Accuracy, AUC and ROC	Shallow	Malaria control
(Brown et al., 2020)	Short term prediction of malaria prevalence	Clinical data from the pediatrics dept. and primary health care centres university of Ibadan	GLM, ensemble method, SVM	MAE, MSE, PCC	Shallow	Malaria control

HMIS = Health Management Information System, NIH = National Institutes of Health, C5.0 = specific decision tree algorithm, ANN = Artificial Neural Network, k-NN = K-nearest Neighbor, LR = Linear Regression, AUC-ROC = Area Under Curve-Receivers operating Characteristics, GaussianNB = Gaussian Naive Bayes, RF = Random Forest, RMSE = Root mean Square Error, MAE = Mean Absolute Error, MSE = Mean Squared Error, OneR = One Rule, ZeroR = zero Rule, NN = Neural Network, GRNN = Generalized Regression Neural Network, GPR = Gaussian Process Regression, SVR = Support Vector Regression, RBNN = Radial Basis Neural Networks, PSO = Particle Swarm Optimization, MLP = Multilayer perceptron, GB = Gradient boosting, GP = Gaussian process, GNB = Gaussian naïve bayes, LDA = linear discriminant analysis, RFR = Random Forest Repressors, EXGBoost = Extreme Gradient Boost, GLM = Generalized Linear Model, PCC = Pearson Correlation Coefficient.

3. DISCUSSION

3.1. Gaps identified in the studies

Despite the advancement in machine learning approaches/algorithms and open access platforms to implement the shallow and deep learning algorithms to improve the accuracy of data-driven systems, its application towards the eradication of malaria burden is still underutilized in addressing malaria control, diagnosis, and drug development. Therefore, this section focuses on the research gaps that need to be addressed to enhance the effectiveness and applicability of these soft computing tools/ algorithms in the necessary in the eradication of malaria burden in terms of control and diagnosis. This challenge is further exacerbated by the following points, namely.

3.2. Non-availability of quality data

Several malaria-endemic regions lack comprehensive and high-quality data to develop machine learning models resulting in sparsity of data. Therefore ensuring effective methods of data collection, preprocessing, and standardization is necessary to ensure availability, consistency, and balanced data. Also, the performance of the machine learning model relies on structured data to generate reliable evidence from the raw data collected with various devices across the malaria endemic regions to improve the output machine learning models. In the generation of evidence to support malaria control, data to estimate the malaria burden with statistical modeling using direct and indirect costs (Affiah et al., 2022; Ayogu et al., 2021; Tefera et al., 2020) is sought from survey data conducted by public health workers. However, a section of the data from the repository covering socioeconomic factors is filtered for model design and implementation due to the inadequacy of its model to cope with high dimensional features. In Affiah et al. (2022) and Tefera et al. (2020), statistical modeling was performed using direct and indirect cost features, without the consideration of geospatial, and socio-demographic features in the data.

Apart from the existing studies on statistical modeling using survey data, meteorological/ climatic data using shallow machine learning (Taconet et al., 2021) or deep learning (Hoyos & Hoyos, 2024), meteorological data (Khan et al., 2024), and a combination of both meteorological and clinical data (Sahu et al., 2023) and incidence data (Mokuolu et al., 2023) are used with machine learning algorithms to implement data-driven models for malaria control (Nkiruka et al., 2021). In the eradication of burden through informed diagnosis, clinical data have been exploited by researchers to train machine learning algorithms using images of leucocyte samples to detect parasites (Hoyos & Hoyos, 2024; Qadri et al., 2023; Shi et al., 2020; Maturana et al., 2023). Apart from inconsistencies associated with data obtained from different collection tools, the unstructured and unbalanced nature of the data can degrade the performance of the learning model. Therefore to implement a machine learning model devoid of bias, adequate data preprocessing and standardization processes should be ensured adopted by the research community.

Also, a holistic approach for adequate integration of data via real-time data fusion from multiple sources can ensure uniformity of format from different data collection subsystems (e.g., climate, socio-economic, health system) to improve predictive models and strategic interventions.

3.3. Inadequate transparency of machine learning models

From the tables of literature (Tables 1, 3-6) summarizing the estimation of malaria burden, malaria diagnosis, and predictive systems in malaria control and diagnosis, it is evident that statistical modeling and shallow and deep learning algorithms are mainly used in the reviewed articles. The shallow learning algorithms among others include; Naïve Bayes, Random Forest (Barraclough et al., 2024; Ahmad et al., 2023), stacking ensemble and neural network (Shi et al., 2020; Jimoh et al., 2022), C5.0 Decision tree, Artificial neural network, K-nearest neighbor, Support Vector Machine, bagging (Khan et al., 2020; Khoirunnisa & Ramadhan, 2023). Similarly, deep learning algorithms are GRU, LSTM, BiLSTM (Dev et al., 2024), and CNN (Kumar et al., 2023). Yolov8, Yolov 5, masked R-CNN, ResNet5.0 (Maturana et al., 2023; Loh et al., 2021; Liu et al., 2023; Hoyos & Hoyos, 2024). However, recent AI algorithms are underutilized to enhance transparency in model procedures as well as malaria control and diagnosis.

For instance, the use of eXplainable and generative AI could present a white-box approach to the current black-box approach in model implementation and the interpretation of output to provide precise evidence for accurate malaria control, diagnosis, and drug development. eXplainable AI (Chaddad et al., 2023), though intended to provide transparent machine learning procedures for accurate interpretation of the learning process is under-utilized in the eradication of malaria burden in terms of control and diagnosis. The transparency of the machine learning models could be defined such that it takes into account the local knowledge and practices of specific regions by aligning with the specific contexts of the region. Out of the final full-length 61 articles reviewed, only one article adopted Shapley Additive Explanation (SHAP) and Local Interpretable Model-agnostic and Large Language models (Attai et al., 2022; Rajab et al., 2023; Taconet et al., 2021). The focus of the adopted models towards the eradication of malaria burden is tailored towards the enhancement of the interpretability of the deep learning model of prediction of malaria diagnosis.

However, there was no concept of transparency defined that is tailored towards providing evidence to eradicate the malaria burden in terms of prevention and control.

Tab. 5. Summary of existing studies on application of machine learning in eradication of malaria burden using detection models

Ref	Objective	Data source	Algorithm	Parameter	Approach	Significance
(Genetu et al., 2023)	Detection of malaria parasites using web-based blood smear images	Malaria Cell Images from patients	DCN and TL with VGG19, Xception and InceptionV3 models	Accuracy	Deep	Malaria diagnosis
(Khoirunnisa & Ramadhan, 2023)	Detection of malaria	Patient data, Indonesia	Bagging (Bootstrap Aggregating), DT	Accuracy	Shallow	Malaria diagnosis
(Rismayanti, 2024)	Detection of malaria using blood smear images	NIH	DT	Accuracy, Precision, Recall, F-Measure	Shallow	Malaria diagnosis
(Aravinda et al., 2023)	To enhance robustness and generalization of machine learning model	Infected and uninfected samples	XGBoost, SVM, and NN classifier	Accuracy, F1-score, precision, recall	Dhallow	Malaria diagnosis

Tab. 5. Summary of existing studies on application of machine learning in eradication of malaria burden using detection models, continuation

Ref	Objective	Data source	Algorithm	Parameter	Approach	Significance
(Vallinayagam et al., 2021)	Identification of infected falciparum malaria parasite	Image data	TL approach VGGN and Support Vector Machine (VGG-SVM).	Accuracy, F1-score, precision, recall, AUC	Deep	Malaria diagnosis
(Comert et al., 2020)	Detect malaria outbreak	Malaria data samples	RDT, logistic regression, and GP	Accuracy	Shallow	Malaria control
(Mwanga et al., 2019)	Detect malaria from rapid blood spots.	Blood samples collected taken from finger pricks	Logistic regression, kNN, SVM, NB, XGBoost, MLP, RF	sensitivity, specificity, positive predicted value, negative predicted value, PRC	Shallow	Malaria diagnosis
(Dev et al., 2024)	Detect malaria	ListerHill National Center for Biomedical Communications	GRU, LSTM, and BiLSTM and candidate RNN classifiers.	Accuracy, precision, recall, F1-score	Deep	Malaria diagnosis
(Bhuiyan & Islam, 2023)	Detect malaria using red blood cells	Microscopic red blood cell images from the NIH repository	VGG16(Retrained), VGG19(Retrained), and DenseNet201(Retrained), custom CNN. Transfer Learning, CNN machine	Accuracy, precision , recall	Deep	Malaria diagnosis
(Kumar et al., 2023)	Detect malaria	Uninfected and infected images from NIH	CNN	Accuracy, precision , recall	Deep	Malaria diagnosis
(Loh et al., 2021)	Early diagnosis of malaria	Uninfected and infected red blood cells	Mask RCNN model, Custom, TL-VGG16, ResNet-50, CNNEx-SVM, R-CNN	Accuracy	Deep	Malaria diagnosis
(Babikir & Thron, 2022)	Detection of malaria	Samples of thin blood smears	Transfer learning	*	Deep	Malaria diagnosis
(Khalighifar et al., 2021)	Multiclass mosquito specie identification system	Spectrogram images	deep-learning algorithms (TensorFlow Inception v3)	*	Deep	Malaria control
(Sriporn et al., 2020)	Detect malaria using thin blood smear images	Image data of thin blood smear	CNN	Accuracy, precision, recall and F1 measure	Deep	Malaria diagnosis
(Yang et al., 2020)	Detect Plasmodium vivax parasites in thin blood smears	Thin blood smear image from patients	Cascading YOLO model and AlexNet classifier	Accuracy, AUC, sensitivity, specificity, precision negative predictive value	Deep	Malaria diagnosis

Tab. 5. Summary of existing studies on application of machine learning in eradication of malaria burden using detection models, continuation

Ref	Objective	Data source	Algorithm	Parameter	Approach	Significance
(Pattanaik et al., 2022)	Detect malaria with mobile microscopy	Phone images of microscopic blood smear	DCNN (i.e. Multi-MMResNet and baseline architectures (Faster RCNN, CNN, LeNet5, AlexNet, GoogleNet, SVM)	Accuracy	Deep	Malaria diagnosis
(Feng et al., 2020)	Detect malaria parasites in thick blood smear images	Thick smear images from patients	Intensity-based IGMS, CNN.	Accuracy, AUC, sensitivity, specificity, precision negative	Deep	Malaria diagnosis
(Rajaraman et al., 2019)	Detect parasitized cells in thin-blood smear images	Giemsa-stained thin-blood smear slidesfrom patients	Custom and pretrained CNNs, Custom CNN, Squeezenet, inceotionResNet-V2, All-ensemble	accuracy, AUC-ROC, MSE, Precision, F-score, MCC	Deep	Malaria diagnosis

DCN = Deep Convolutional Network, TL = Transfer Learning, VGGN = Visual Geometry Group network, RDT = Random Decision Tree, GRU = Gated Recurrent Unit, LSTM = Long Short-Term Memory, BiLSTM = Bi-directional LSTM, DCNN = Deep Convolutional Neural Networks, MMResNet = Magnification Deep Residual Network, IGMS = Iterative Global Minimum Screening, MCC = Matthews Correlation Coefficient.

Tab. 6. Summary of existing studies on application of machine learning in eradication of malaria burden using classification models

Ref	Objective	Data source	Algorithm	Parameter	Approach	Significance
(Muhammad et al., 2024)	Classification and segmentation of malaria cell	Microscopic images of blood cells	DenseNet and EfficientNet models, coupled with a ReLU activation function	Precision, Recall, F1-score	Deep	Malaria diagnosis
(Rosnelly et al., 2023)	Classify the type and stage of development of malaria parasite	*	SVM and CNN	Accuracy	Deep	Malaria diagnosis
(Rashke & Shahzad, 2023)	Classifying malaria-infected erythrocytes (RBCs)	Malaria NIH	Unified SGD, logistic regression, and DT, Xgboost, RF, Multinomial	Accuracy, recall precision	Shallow	Malaria diagnosis
(Iftikhar et al., 2024)	Classification of malaria blood smears from red blood cells	Kaggle	CNN ResNet101, SqueezeNet, LDA	Accuracy (%), Precision (%), Specificity (%), Sensitivity (%), F1-Score	Deep	Malaria diagnosis

Tab. 6. Summary of existing studies on application of machine learning in eradication of malaria burden using classification models, continuation

Ref	Objective	Data source	Algorithm	Parameter	Approach	Significance
(Amin et al., 2023)	Classification of healthy and Plasmodium falciparum-infected cells	Blood smear images from Chittagong Medical College Hospital in Bangladesh	Semi-supervised GAN and TL	Precision, accuracy, sensitivity, F1 score, specificity and AUC-ROC	Deep	Malaria diagnosis
(Atoyebi et al., 2023)	Classification of malaria incidence	Clinical records of public general hospital in Federal Capital Territory, Abuja.	MultinomialNB and RF	Precision, recall, F1-score, accuracy	Shallow	Malaria diagnosis
(Diker, 2022)	Malaria cell image classification	Malaria cell image	Residual CNN, k-NN, and SVM and NCA	Acc, Se, Spe, and F-score	Deep	Malaria diagnosis
(Morang'a et al., 2020)	Multiclass classification of clinical malaria outcomes based on haematological parameters	Navrongo Health Research Centre (NHRC), Northern Ghana.	ANN	Accuracy, Kappa, ROC-AUC, Precision, Recall, F1-Score	Shallow	Malaria diagnosis
(Quan et al., 2020)	Classification of Red Blood Cells in Malaria Diseases	Red Blood Cells (RBC) dataset by USA NIH	ADCN	Accuracy, sensitivity and specificity, F1-score	Deep	Malaria diagnosis

SGD = Stochastic Gradient Descent, GAN = Generative Adversarial Network, NB = Naïve Bayes, NCA = Neighborhood Components Analysis, ACC = Accuracy, Se = Sensitivity, Spe = Specificity, ADCN = Attentive Dense Circular Net.

3.4. Inadequate evaluation parameters to measure the real-world impact of machine learning on malaria control and diagnosis

Performance parameters could provide baseline measures to ascertain the effectiveness of models in real-life applications are yet to be fully developed by researchers. However, the study of Brown et al. (2020) provided an error tolerance range of (+0.1 to -0.05) as an acceptable scale for clinically relevant decision support in holoendemic settings. Other machine learning approaches adopted model evaluation parameters such as: accuracy, precision, recall, specificity, F1-score and more. The summary of the evaluation parameters and their corresponding values derived from malaria control and diagnosis research utilizing both shallow and deep learning models is compiled in Tables 7 and 8.

Tab. 7. Deep learning performance evaluation parameters and values

Ref.	Data size	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision	Recall	F1-score
(Onuche-Ojo et al., 2024)	27,558	97.17	-	-	0.97	0.97	0.97
(Dev et al., 2024)	27,558	96.2	-	-			
(Iftikhar et al., 2024)	27,558	99.73	-	-	-	-	-
(Bhuiyan & Islam, 2023)	27,558	97.92	-	-	0.98	0.98	0.98
(Hoyos & Hoyos, 2024)	333	95	94	93	-	-	-
(Hemachandran et al., 2023)	27,558	97.06	-	-	0.97	0.97	0.97
(Khalighifar et al., 2021)	1,400	94.50	-	-	-	-	-
(Feng et al., 2020)	1819	97.26	78.98	80.81	0.83	0.98	
(Quan et al., 2020)	257558	97.47	97.78	97.07	-	-	-

Tab.8. Shallow machine learning performance evaluation parameters and values

Ref	Data size	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision	Recall	F1-score
(Khan et al., 2024)	4428	99.8	100	98.3	-	-	-
(Onyijen et al., 2023)	856	98.3	-	-	-	-	-
(Khoirunnisa & Ramadhan, 2023)	337	82	56.93	-	-	-	-
(Jimoh et al., 2022)	1,200	85.6	84.06	86.09	-	-	-
(Mariki et al., 2022)	2556	79	82	69	0.71	0.76	-
(Shi et al., 2020)	217	94.58	93.82	94.95	-	-	-
(Mwanga et al., 2019)	296	-	91.7	92.8	-	-	-

Based on Tables 7 and 8, studies by Bhuiyan & Islam (2023), Onuche-Ojo et al. (2024), Iftikhar et al. (2024), and Quan et al. (2020) indicate a significant trend in malaria control and diagnosis, suggesting that larger sizes of data enhance the performance accuracy of both shallow machine learning and deep learning models. For instance the maximum and the minimum sizes of data utilized for malaria control and diagnosis using deep learning is 27,558 and 337, respectively. Conversely, smaller datasets tend to correlate with lower performance accuracy in deep learning applications For instance, a comparison of the size of data in the study of Hoyos & Hoyos (2024) and Khalighifar et al. (2021) with the data size of 333 samples recorded 95% accuracy, whereas similar study by Iftikhar et al. (2024) with the data size of 27,558 samples recorded 97% accuracy in deep learning.

Also, it has been observed that the data sizes utilized in shallow machine learning are generally smaller than those required for deep learning tasks. For instance, the maximum and minimum data sizes for malaria diagnosis using shallow learning have been recorded at 4428 (Khan et al., 2024) and 217 (Shi et al., 2020) samples, respectively, which may be inadequate for effective deep learning modeling. This analysis indicates that the application of deep learning compared to shallow learning is contingent upon the dimensionality of the data as well as the availability of advanced computational resources for the generation of precise evidence towards eradication of malaria burden in terms of control and diagnosis.

3.5. Limitations of the study

This review focuses on research articles published between 2018 and 2024, utilizing databases indexed by Google Scholar, PubMed, and Science Direct. It is important to recognize that articles published beyond this specified period, as well as those from conferences not indexed by Springer, ACM, or IEEE, are excluded from the analysis. Additionally, findings from journals and proceedings not written in English were also excluded from consideration. Consequently, there is a potential for relevant articles to be overlooked due to the limitations of the search queries used for document retrieval. To enhance the robustness of future reviews, it would be beneficial to expand the scope to include other databases and indexes and consider studies in additional languages. Addressing these factors may mitigate bias and provide a more comprehensive understanding of the research landscape.

3.6. Future work

Future research initiatives should prioritize the adoption of standardized methodologies to investigate both shallow and deep machine learning techniques. Additionally, incorporating data from publications written in languages other than English could significantly reduce potential biases identified in this review, thereby enriching the overall analysis. It is imperative to examine the barriers to the application of machine learning in malaria control and diagnosis, including issues related to data quality, insufficient infrastructure, and a shortage of expertise in resource-limited settings. Conducting thorough meta-analyses to assess the effectiveness of machine learning (ML) and deep learning (DL) algorithms in malaria diagnosis and control will provide valuable insights for the field. Furthermore, exploring the integration of machine learning techniques with advanced technologies, such as Internet of Things (IoT) devices and geographic information systems (GIS), holds great promise for enhancing real-time data collection and surveillance. Pursuing these avenues for future research could substantially advance capabilities in malaria control and contribute to improved health outcomes.

4. CONCLUSION

Improving the quality of evidence through the application of machine learning can engender support for malaria control and diagnosis through real-time informed decision-making and policy formulation. From statistical modeling to shallow and deep learning algorithms in the eradication of malaria burden on households, the application of varying data analytics approaches is targeted towards the refinement of evidence. The evidence from machine learning is measured in terms of reduced error rates with parameters such as RMSE, MAE, MAPE, correlation coefficients, and more). In this review, a scoping review of literature has revealed the dearth of literature on the application of machine learning in malaria control measures (e.g. estimation of cost of malaria burden and surveillance), despite the availability of data from malaria indicator and demographic health surveys. This lapse has contributed to the increased malaria burden among households, despite interventions by government and donor agencies especially in sub-Saharan Africa.

However, studies using machine learning in malaria diagnosis are widely researched between 2018-2024, inclusively but mostly at experimental stages without model deployment to provide real-time information required for the speedy attainment of SDG targets towards sustainable good health and well-being. Also, the need for collaboration among Computer Science, public health enumerators, and medical specialists which is currently lacking in the existing studies should be explored in further development of predictive systems for malaria control and diagnosis using machine learning. These research gaps can serve as an open problem for researchers to explore taking into cognizance the limitations associated with machine learning algorithms/ models and predictive systems.

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Author Contributions

The first author has done research conceptual framework, article collection, methodology, result evaluation, and drafted the manuscript. The second author supervised manuscript review and editing.

Conflicts of Interest

The authors declare that they have no financial or non-financial interests related to this study. Also, there was no conflict of interest between authors or any other group to influence the work reported in this paper.

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