Sensing and Imaging (2024) 25:55
https://doi.org/10.1007/s11220-024-00503-3

RESEARCH

Smart Malaria Classification: A Novel Machine Learning Algorithms for Early Malaria Monitoring and Detecting Using IoT-Based Healthcare Environment

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Received: 17 June 2024 / Revised: 19 July 2024 / Accepted: 5 August 2024 /
Published online: 9 September 2024

Abstract

Malaria, caused by the Plasmodium parasite and transmitted by female Anopheles mosquitoes, poses a significant risk to nearly half of the global population, with sub-Saharan Africa being the most affected. A rapid and accurate detection method is crucial due to its high mortality rate and swift transmission. This study proposes a real-time malaria monitoring and detection system using an Internet of Things (IoT) framework. The system collects real-time symptom data via wearable sensors, employs edge computing for processing, utilizes cloud infrastructure for data storage, and applies machine learning models for data analysis. The five key components of the framework are wearable sensor-based symptom data collection and uploading, edge (fog) computing, cloud infrastructure, machine learning models for data analysis, and doctors (physicians). The study compares four machine learning techniques: Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), and Naïve Bayes. SVM outperformed the other algorithms, achieving 98% training accuracy, 96% test accuracy, and a 95% AUC score. Based on the findings, we anticipate that real-time symptom data would enable the proposed system can effectively and accurately diagnose malaria, classifying cases as either Parasitized or Normal.

Keywords Malaria · Internet of Things · Machine learning · Early identification · Real-time monitoring

Extended author information available on the last page of the article

1 Introduction

Malaria is a potentially fatal disease conveyed to people by certain types of mosquitos. It is found primarily in tropical nations [1, 2]. According to a World Health Organization (WHO) report, this condition affects hundreds of millions of individuals each year. The World Malaria Report predicts a rise in malaria cases from 244 million in 2021 to 249 million in 2022 [2]. Aside from the disruptions caused by COVID-19, the global malaria response has faced an increasing number of challenges, including drug and insecticide resistance, humanitarian crises, resource constraints, climate change impacts, and delays in program implementation, particularly in high-burden countries. Malaria is primarily transmitted to humans through bites from infected female Anopheles mosquitoes, blood transfusions, and infected needles [3]. Malaria has long been recognized as one of the leading causes of outpatient visits, hospitalizations, and fatalities across all age groups.

Malaria, a preventable disease, can be controlled and prevented by employing appropriate methods and protocols, including early detection of the malarial parasite [2]. For examining malaria utilizing thick or thin blood smears [4], several laboratory techniques such as polymerase chain reaction (PCR) [5], microscopy, and rapid diagnostic test (RDT) [6] are often utilized and recommended by WHO protocol. Therefore, early malaria identification is critical for successful treatment and death prevention, resulting in reduced malaria transmission. We are therefore driven to create malaria diagnosis protocols that are both quicker and more precise. Recently, there has been a lot of research interest in machine learning (ML) architectures with the Internet of Things (IoT). These architectures are the most important way to automatically and more precisely diagnose disease.

The Internet of Things (IoT) is a network of interconnected smart objects that enables virtual communication between people and things to provide necessary services at any time [7]. IoT technologies are already being used in healthcare to improve patient care and results, opening up new possibilities for remote monitoring [8–10], individualized medical plans of treatment [11, 12], and efficient healthcare delivery [13, 14]. As a result, IoT aids in the delivery of effective and efficient care by revolutionizing traditional healthcare systems by providing an integrated system of care and accurate diagnosis, sharing effective health strategies across locations, providing effective and customized treatment planning, and gaining insight from data collected.

In addition to improving patient care, the IoT has the potential to significantly cut healthcare costs by streamlining operations, automating routine tasks, and reducing the need for costly interventions. It improves patient care by enabling real-time data gathering and monitoring, resulting in faster response times, better patient outcomes, tracking the spread of disease, and cost savings. Furthermore, usual duties such as vital sign monitoring and prescription delivery can be automated, lessening the chance of errors and labor expenditures. Most importantly, IoT's early malaria detection and continuous monitoring capabilities aid in the prevention of costly medical consequences, the reduction of hospitalizations, and the reduction of the need for costly therapies, ultimately lowering healthcare costs dramatically.

IoT and machine learning have been applied in many domains, including smart cities [15], information and network security [16], agriculture [17, 18], healthcare

[19] malaria detection [20, 21], and so on. Many scientists are pushed to develop an automatic diagnostic system since earlier malaria identification can boost patient survival rates.

In previous years, there have been several studies in the field of IoT and machine learning for malaria detection. The study conducted by Meraj et al. [22] focused on analyzing the use of machine learning algorithms in Python for predicting malaria. Additionally, the study explored the adaptability of Internet of Things (IoT) technology in this context. A fog computing-based intelligent healthcare system is presented by Logesh et al. [23] to detect and prevent illnesses spread by mosquitoes. The study by Sabukunze et al. [24] proposes an Internet of Things design for smart monitoring and alert systems for malaria patients in Burundi. Mehdi et al. [25] proposed the use of the Internet of Things for chronic disease management. The study presents an overview of the usage of IoT for chronic disease management, followed by a ranking of different chronic diseases in developing nations depending on their priority for employing IoT. The investigation into IoT and machine learning for malaria detection suggests a favorable trend in leveraging advanced technologies for healthcare applications. This demonstrates a promising development in enhancing healthcare through inventive methods.

From this work, we suggested a technique to detect malaria early that utilizes machine learning and the IoT. The suggested system will be made to examine the fifteen main signs and symptoms of malaria. The system may recognize trends and forecast outcomes by utilizing machine learning algorithms on the gathered data from the Internet of Things devices and enabling early identification by classifying the cases as parasitized or normal. This strategy may enhance malaria early diagnosis and ultimately result in lifesaving.

This study presents a malaria detection and smart health monitoring system based on wearable sensor technology that collects real-time symptoms. The study proposes the use of four machine learning methods: Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbor (K-NN), and Naïve Bayes, for identifying probable malaria symptoms in real-time and classifying the cases as parasitized or normal. Machine learning algorithms are crucial for healthcare IoT due to the large amount of real-time data generated by devices, enabling meaningful information extraction and high accuracy when trained correctly. This detection and monitoring system might be used in conjunction with an IoT infrastructure to track both potential and confirmed instances of malaria, as well as the treatment responses of individuals who recover from malaria. Aside from real-time monitoring, this system could help to understand the nature of malaria by collecting, evaluating, and preserving essential data. This study aims to improve the accuracy and speed of malaria detection, ultimately reducing the disease's impact on affected populations. The following are the primary contributions of our work:

- Determining the role of development innovations such as the IoT with machine learning for early malaria treatment and elimination.
- The significance of machine learning algorithms in anticipating future phases of malaria illnesses, preventing disease transmission has been studied, and classifying the case into parasitized or normal.

- Identification of suspected malaria symptoms at an early stage through data analysis.
- The suggested IoT framework is evaluated for practicality and dependability using a variety of performance measures.
- Evaluation and comparison of those four algorithms to identify the most effective method for diagnosing malaria.
- The SVM algorithm obtained 98% training accuracy, 96% test accuracy, and 95% AUC score.

The structure of this document is as follows. Section 2 describes the paper's methods, including the proposed framework IoT with ML model. This section also goes over the dataset that was used to train and evaluate the four ML models. Section 3 shows performance evaluation techniques. Section < link rid="Sect. 15”>4</link>, and 5 displays the outcomes of each model and discussion respectively. Section 6 concludes the research study.

2 Methods

2.1 The Internet of Things Background

The Internet of Things refers to both the technology that allows devices and the cloud to communicate with each other as well as the overall network of linked items. The perception (sensor) layer, connection (network) layer, data processing layer, and user interface (application) layer are the four essential building blocks of an Internet of Things implementation [26].

Perception (Sensing) Layer The sensor layer serves as the foundation of an IoT system. It consists of sensors and actuators that collect and analyze data from outside sources [27]. This layer is critical in gathering raw information from physical settings for higher framework-level analysis. These sensors can be incorporated into medical apparatus, wearable technology, and human bodies. This network consists of data-communicating sensors and smart devices [28].

Connectivity (Network) Layer The ability for digital data to flow across all components of an Internet of Things architecture depends on the network layer sometimes referred to as the transport or device layer. One or more communications networks must be in place to facilitate data interchange among sensors, actuators, wearables, the IoT platform, and gateway components [28]. For example, cellular networks, Bluetooth, WI-FI, Radio Frequency Identification Devices (RFID), Zigbee, and Bluetooth are essential for facilitating data exchange between IoT devices and medical practitioners.

Data processing Layer The data processing layer processes and analyzes gathered data to support decision-making and operational efficiency for enterprises. Through the application of ML algorithms, it is able to process raw data from IoT systems and preserve essential features that are utilized for automated decision-making. An important first step toward more optimized outcomes produced by IoT systems using collected data is the successful implementation of these measures, which translates into efficient real-world results by enhancing the quality insights obtained from the obtained raw data into effective actions according to what is needed at hand [26].

User Interface (Application) Layer In an Internet of Things design, the user interface (application) layer provides a crucial means for users to communicate with the system and access particular functions [29]. This makes it easy for consumers to use their gadgets, whether they are utilizing computer dashboards that are centrally located or mobile apps. When someone utilizes an app made especially for smart homes, this can be an example [27].

2.2 The Proposed IoT Framework

The proposed IoT-based system, which might be used to track and recognize (forecast) possible malaria symptoms in real time, is shown and discussed in this part. Our suggested IoT architecture's framework is depicted in Fig. 1. It is composed of five primary parts: an interface for symptom data collection and uploading, an edge (fog)

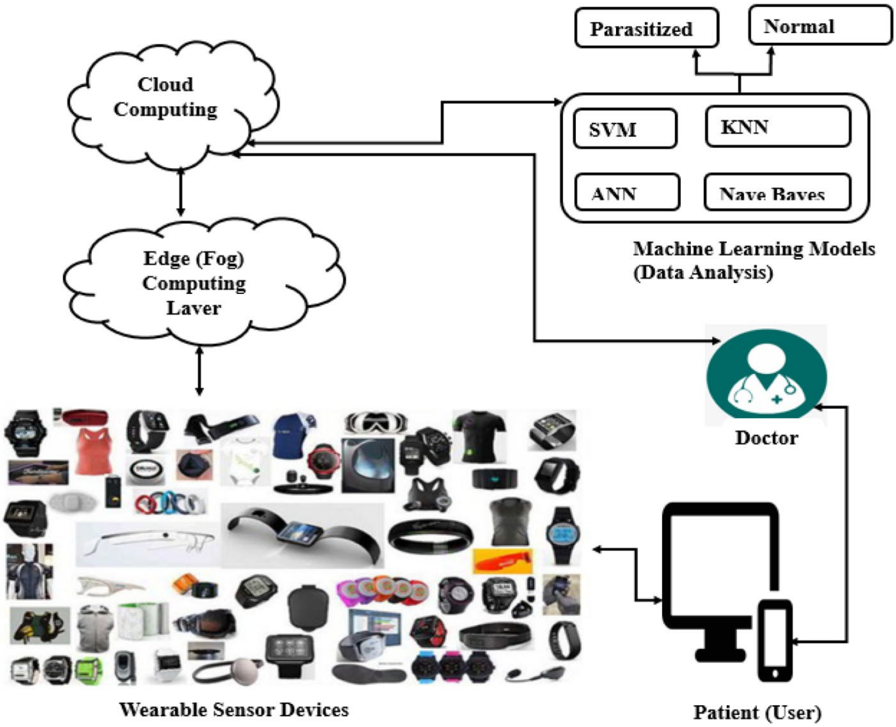

Fig. 1 Overall IoT using machine learning-based framework for early identification and monitoring of malaria

computing layer, cloud computing, machine learning, and health physicians. These parts are connected by a cloud infrastructure.

2.2.1 Symptom data Collection and Uploading Using Wearable Devices

In the battle against this fatal illness, gathering and uploading data on malaria symptoms via the Internet of Things is essential. We can collect real-time data on the symptoms that malaria patients are experiencing by employing Internet of Things technologies. The first step in the process is gathering data from multiple sources, including smartphone apps, wearable technology, and remote monitoring systems. These gadgets have sensors built in to identify common malaria symptoms like fever, chills, headaches, and exhaustion. These symptoms can be detected by a variety of biosensors. As an example, sensors can be used for the detection of fever [30], IoT-based wearable devices to monitor the signs of cold [31], rigor activity monitoring systems by integrating IoT sensors [32], Motion-based and heart-rate sensors can be used to detect fatigue [33], using sleep time data from wearable sensors for headache [34], Bittertongue, Body sensors are embedded in the user's body to capture vomiting [35], IoT in medical diagnosis diarrhea [36], we can also use [37, 38] to detect Convulsion, Anemia, Jaundice, Cocacola-Urine, Hypoglycemia, Prostration, and Hyperpyrexia of malaria symptoms.

The particular types of IoT wearable sensors are used to track several malaria signs at the moment. To identify fever, temperature sensors such as thermistors and infrared sensors are used to continuously measure body temperature. To track chills, skin conductance sensors such as Galvanic Skin Response (GSR) sensors detect variations in skin conductance. To measure rigor activity and tiredness, accelerometers, and gyroscopes more especially, MEMS accelerometers and gyroscopes track movement and orientation. Heart rate variability is measured by heart rate monitors employing Photoplethysmography (PPG) sensors to identify physical stress and fatigue indicators. Electromyography (EMG) sensors, in particular surface EMG sensors, track muscular contractions in order to identify seizures and rigor. Vomiting and diarrhea episodes are monitored by gastrointestinal activity sensors, which include ingestible sensors and abdominal wearables. Furthermore, blood oxygen and glucose monitors, such as continuous glucose monitors and pulse oximeters, evaluate blood oxygen levels and glucose to identify jaundice, hypoglycemia, and anemia.

Following collection, the data is transferred to the IoT platform for processing and analysis. To find patterns and trends in the data and aid in the early diagnosis and containment of malaria epidemics, sophisticated machine learning algorithms are employed. Real time monitoring of malaria symptoms is made possible by the Internet of Things platform, which helps medical professionals to act swiftly and promptly. By doing so, the disease's severity can be considerably decreased, and patient outcomes can be enhanced. IoT devices also make remote monitoring possible, which is especially helpful in places where access to medical institutions is restricted. Without needing to see medical professionals in person, patients can track their symptoms using wearable technology or smartphone apps and share the information with them.

2.2.2 Edge (fog) Computing Layer

Edge computing, also known as fog computing, is a decentralized system of processing and storing data close to its source, which speeds up reaction times and improves network device performance overall. Performance can be maximized and latency can be significantly reduced by minimizing remote information transfer [39]. This distributed model is particularly important for Internet of Things systems that need to respond in real-time. That is, if sensors detect an irregularity in data packets being collected and sent from edge devices, they can take immediate corrective action or halt execution without having to wait for a response.

In the proposed study, data from various IoT wearable sensors, such as temperature sensors, heart rate monitors, and accelerometers, is initially processed locally at the network's edge. This local processing includes preliminary data analysis, filtering, and aggregation to discover any immediate anomalies or trends that may indicate malaria symptoms. By processing data locally, the system can take immediate corrective action or halt execution if abnormalities are found, rather than waiting for a response from a central server. This decreases latency and enables early treatments, which is critical for real-time monitoring and quick response to potential malaria cases. Moreover, the implementation of edge computing greatly strengthens the confidentiality and integrity of data in IoT healthcare infrastructures [28], and is partially analyzed closer to its source, reducing the risk associated with transferring large volumes of raw data over the network. Edge computing also makes it possible to operate offline and be resilient to network outages [40].

Once the preliminary processing is completed, the refined data is transferred to the cloud for further analysis and long-term storage. This strategy maximizes system efficiency by limiting the quantity of data transmitted to the cloud, lowering bandwidth utilization and associated expenses. It also ensures that essential health data is promptly acted upon, so improving patient outcomes and allowing healthcare providers to respond more effectively to emerging health risks.

2.2.3 Cloud Infrastructure

The cloud offers a platform for handling [41], storing [42, 43], and analyzing massive volumes of medical data produced by Internet of Things (IoT) devices [44]. In the context of the Internet of Medical Things, healthcare providers can lower costs, improve patient outcomes, and raise the standard of care by storing and processing medical data on cloud computing systems. For example, in this framework, the cloud infrastructure is connected to the Internet and enables users to submit real-time symptom data. It also keeps track of each user's unique health information, shares prediction results, transmits doctor advice, and stores data. Healthcare providers can save money, enhance patient outcomes, and improve the overall quality of care by storing and processing medical data on the cloud. In our work, the cloud infrastructure is networked via the internet and (1) allows each user to upload real-time symptom data, (2) edge can be maximized and latency can be significantly reduced by minimizing remote information transfer, (3) maintains personal health records, (4) communicates prediction findings, (5) communicates physician suggestions, and (6) offers information storage.

2.2.4 Machine Learning Models for Analysis and Classifying the data

Machine learning models are becoming an essential component of the Internet of Things ecosystem. With the large amounts of data created by IoT devices, these models are critical in processing and evaluating the data [45]. The integration of machine learning and IoT enables the development of intelligent systems capable of making accurate predictions and judgments based on data acquired [46]. These models are trained to spot patterns and trends using powerful algorithms, allowing them to deliver significant insights and recommendations. Machine learning models can be taught to discover patterns and anticipate the spread of the disease by gathering data on malaria symptoms from IoT devices, and enabling early identification by classifying the cases as parasitized or normal. This can assist healthcare practitioners in better understanding malaria epidemiology and developing more effective treatment strategies. We can hope to achieve substantial advances in the fight against this fatal disease by harnessing the power of machine intelligence and IoT. One of the primary benefits of employing machine learning in conjunction with IoT is the capacity to manage enormous volumes of malaria symptom data in real time. IoT devices generate vast amounts of data every second, and traditional data analysis approaches simply cannot keep up. Therefore, machine learning algorithms are intended to manage such large amounts of data and can process it in real-time, allowing for faster and more accurate analysis.

In our proposed work, in addition to creating a malaria model, these machine-learning techniques offer a real-time dashboard with the processed data. The model might subsequently be applied to rapidly detect or forecast possible instances of malaria by using real-time data that users upload and collect. The patient's reaction to therapy can also be predicted by the model.

2.2.5 Doctor (Health Physicians)

Doctors, particularly physicians, play an important role in monitoring possible malaria cases. They can closely monitor individuals whose real time uploaded malaria symptom data suggests a possible infection by using our suggested machine learning-based identification and prediction model. This proactive method enables doctors to respond to suspected cases quickly by doing additional clinical investigations to confirm the presence of malaria. Doctors can accurately diagnose and isolate confirmed cases by quickly following up with additional testing and assessments. This is critical in preventing illness spread and delivering adequate healthcare to individuals affected. This will allow verified patients to be identified and treated appropriately. We can use this approach to ensure that malaria cases are recognized and treated as soon as possible, lowering the risk of killing and improving patient outcomes. It represents a step forward toward a more efficient and effective healthcare system. We hope to drastically reduce the incidence of malaria by promoting early detection and intervention through the collaborative efforts of doctors and our machine-learning model. We can effectively combat this infectious disease and enhance general public health by leveraging technology and medical expertise.

2.3 Workflow of the Framework

The program workflow shows the phases in a step-by-step series of instructions, workflow, or process. The process (scenario) that the framework uses, is best explained as follows.

1) The system uses wearable technologies and sensors to collect real-time patient symptom data, including fever, cold, exhaustion, headache, diarrhea, vomiting, convulsions, anemia, jaundice, hypoglycemia, prostration, and hyperpyrexia.
2) The machine learning data analysis center receives the identified malaria symptom data via wearable technology and a smartphone, which are transmitted via cloud infrastructure and the edge (fog) computing layer. Furthermore, the digital records of the health center are regularly transmitted to the machine learning data analysis center via cloud infrastructure and the edge computing layer.
3) If a possible case is identified, it will be sent to the relevant doctor for additional examination. After that, the patient will be notified and allowed to visit the medical institution for clinical testing, which includes the diagnosis of malaria using rapid diagnostic tests, polymerase chain reactions, and thick or thin blood smears.

2.4 Forecasting Potential Cases

This section covers the machine learning techniques and prediction models that would be applied in the collected malaria symptom data analysis center of the proposed IoT-based infrastructure. In specifically, an experiment was conducted to assess the viability of using machine learning algorithms for early identification (or prediction) of potential malaria infections. This section's remaining content presents and examines the experimental setup and results.

2.4.1 Dataset

A dataset of 1011 malaria cases from Nigeria's Federal Polytechnic Ilaro Medical Centre, including 15 symptoms, was used for machine learning techniques to analyze the cases available at: https://doi.org/10.1016/j.dib.2019.104997. Furthermore, we formatted the data well for the usage of machine learning techniques [47].

2.4.2 Data Preprocessing

The data was preprocessed and formatted to make it more suitable for machine learning. There are 1011×15 data records in the preprocessed dataset. Of those, 663 records were to non-confirmed cases of malaria, and 348 records related to confirmed cases. A variety of similarity metrics are utilized, including the Pearson correlation coefficient, Cosine similarity, and Jaccard similarity coefficient. To classify malaria infections based on indications (symptoms), the Jaccard similarity coefficient is preferable to the Pearson correlation coefficient and cosine similarity. Because all of the attributes (symptoms) are binary, i.e. the existence or absence of symptoms.

3 Performance Evaluation

An assessment metric's main objective is to evaluate the suggested intelligent system's effectiveness. The success of the categorization system may be evaluated using a variety of assessment metrics. Several assessment measures, including accuracy, precision, recall or sensitivity, area under the curve (AUC) score, confusion matrix, and F1-score, can be used to examine the effectiveness of classification.

Precision-Recall Curve Precision-Recall is a useful measure of success of prediction when the classes are very imbalanced. In information retrieval, precision is a measure of result relevancy, while recall is a measure of how many truly relevant results are returned.

4 Results and Discussion

This preprocessed dataset was used to develop a predictive model for our malaria detection (prediction). This model's job is to assess the chance that a particular person is infected with malaria. Four machine learning methods, including Support Vector Machine, Neural Network, Naïve Bayes, and K-Nearest Neighbor have been utilized for this purpose. To conduct experiments, we utilized a Google compute engine instance called Google collaboratory (colab). The Colab notebooks used for experimentation were Jupyter-based and functioned similarly, to a Google Docs object. The model was developed using the GPU and Python programming language.

4.1 Support Vector Machine

The support vector machine (SVM) method uses a classifying hyper-plane to split a dataset into two groups, minimizing gaps and claiming maximum range. SVMs are resistant to overfitting and can classify datasets using linear functions or non-linear kernels [48]. Our SVM method has shown impressive results, achieving a training accuracy of 98%, a testing accuracy of 96%, and an AUC score of 95% indicating that the model generalizes well to unseen data. The AUC score is an important parameter when evaluating the performance of a machine learning model, especially for classification tasks. It indicates the model's capacity to distinguish between distinct types of malaria, in this case, parasitized and normal. An AUC score of 95% suggests that the SVM model is quite accurate at recognizing positive (parasitized) and negative (normal) cases. A higher AUC value indicates that the model performs better in predicting positive cases as positive and negative instances as negative. As shown in Fig. 2, the

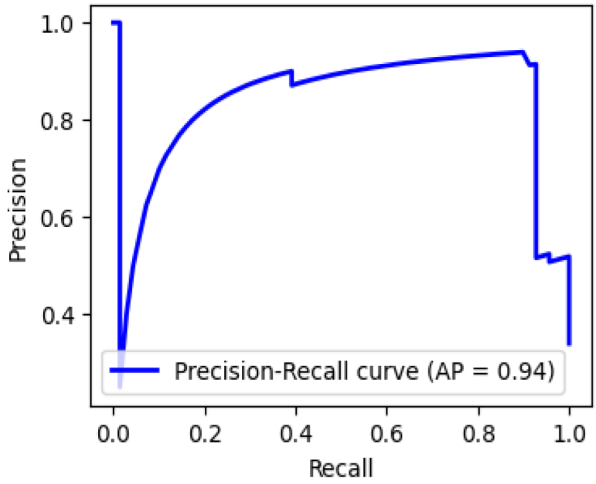

Fig. 2 Precision-Recall curve of the SVM

Precision-Recall curve visually displays the trade-off between precision (the model's ability to properly identify positive cases) and recall (the fraction of actual positive cases that were correctly recognized). Furthermore, the Average Precision (AP) score of 94% indicates the overall precision-recall balance, demonstrating that the model is effective at retrieving relevant instances while retaining a high precision rate. These metrics reflect the model's great performance in malaria detection, demonstrating its ability to accurately and reliably classify malaria cases based on real-time symptom data. The SVM curve has a more gradual decline in precision as recall increases, suggesting the model is better able to balance precision and recall compared to the ANN, and KNN models. As shown in Fig. 3, only 5 out of 69 patients who tested as positive for malaria were mistakenly labeled as uninfected. Similar to this, 128 of 134 normal individuals have received the proper diagnosis. Only 6 patients have ever been misdiagnosed as having malaria. Overall, this SVM method is more accurate than the other experiments.

4.2 Artificial Neural Network

An artificial Neural Network (ANN) is a machine learning model that contains numerous layers for data analysis, an output layer for output delivery, and an input layer for receiving input. This architecture mimics the way the human brain learns [49]. Within ANNs, intermediate inputs are sent via hidden layers that randomly allocate weights and biases to each input. Afterward, multiple weighted sums are computed and passed through layers carrying weights and sums until they reach the final layer, which uses an activation function to determine the output. If the outputs are incorrect, they are propagated backward through the previous layers using a cost function to adjust the weights until correct answers are obtained [50]. During the training process, the ANN model makes use of 100 single hidden layers and a batch size of 32. It also utilizes the Adam optimizer with a learning rate of 0.001 and a maximum of 400 iterations. The ANN method has achieved a training accuracy of 97% and a testing accuracy of 90%. Additionally, the ANN approach has shown excellent results,

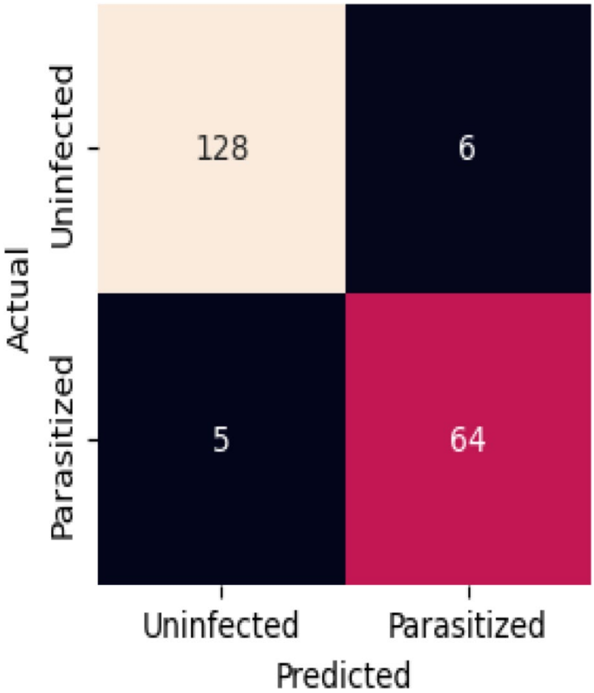

Fig. 3 Confusion matrix of SVM method

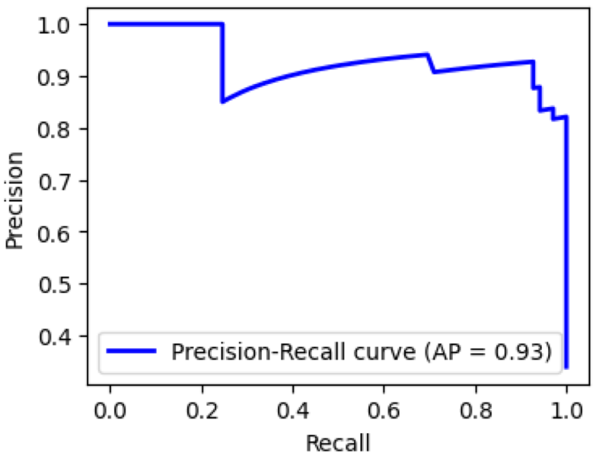

Fig. 4 Precision-Recall curve of ANN

outperforming the other with an AUC score of 97%. Figure 4, depicts the Precision-Recall Curve of an ANN model, a standard performance evaluation metric used in machine learning and information retrieval tasks. The curve begins with a precision of 1.0 and a recall of 1.0, indicating that the system can initially detect all positive instances with perfect precision. As recall increases, precision eventually diminishes, demonstrating the trade-off between precision and recall. As shown in Fig. 5, only 5 out of 69 patients who tested as positive for malaria were mistakenly labeled as uninfected. Similar to this, 125 of 134 normal individuals have received the proper diag-

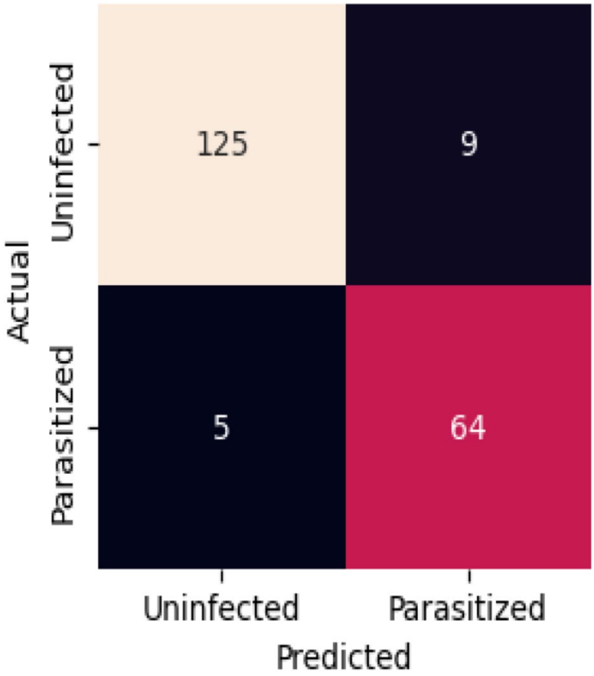

Fig. 5 Confusion matrix of ANN method

nosis. Only 5 patients have ever been misdiagnosed as having malaria. Compared to earlier tests, the accuracy of this ANN approach is lower.

4.3 K-Nearest Neighbors

The k-nearest neighbor's algorithm, also known as KNN or K-NN, is a non-parametric supervised learning classifier that uses similarity to group data points for classification or prediction. For the item whose category is established, distances, mostly Euclidean, are computed to its k nearest neighbors. That is, the distance is calculated by taking the difference between the neighbors' characteristics and adding them together. KNN is extensively utilized in many different applications and is useful at classifying labeled data even in situations when the training set is minimal. Our KNN method has shown impressive results next to SVM, achieving a training accuracy of 97%, a testing accuracy of 91%, and an AUC score of 94%. Figure 6, presents the Precision-Recall Curve of a KNN model. The curve begins at the upper left corner, with a high precision that gradually decreases as recall increases, As memory increases, precision eventually diminishes, resulting in the typical curve shape. The blue line depicts the Precision-Recall curve, and the area under the curve (AP) is 90%, suggesting that the model is doing well. As shown in Fig. 7, only 18 out of 69 patients who tested as positive for malaria were mistakenly labeled as uninfected. KNN performs worse than SVM and ANN, and better than Naïve Bayes when compared to each other.

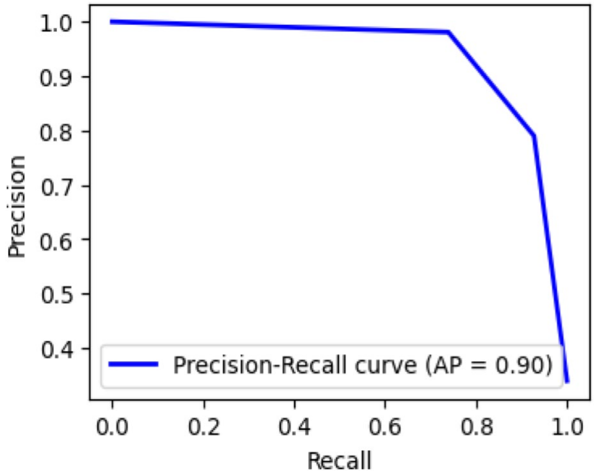

Fig. 6 Precision-Recall curve of KNN

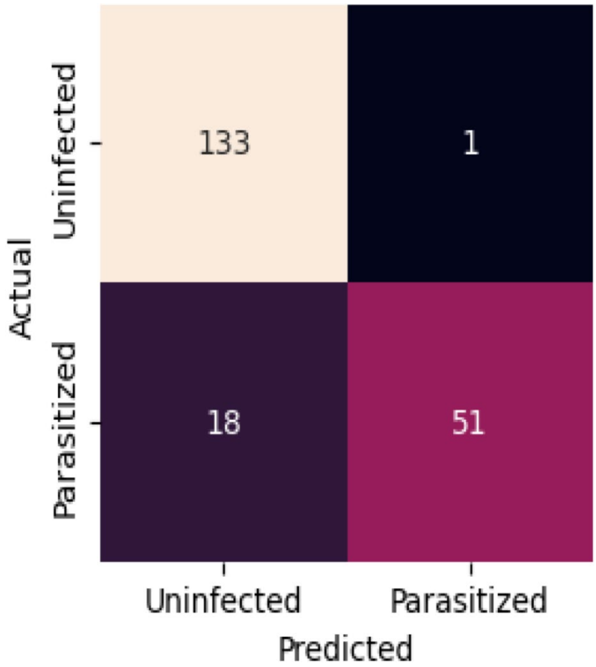

Fig. 7 Confusion matrix of KNN method

4.4 Naïve Bayes

A popular supervised machine learning method for classification issues such as text categorization is the Naïve Bayes classifier. Given that it is a generative learning algorithm, it is likely to replicate the input distribution for a given class or category. This approach is predicated on the idea that, given the class, the properties of the input data are conditionally independent, enabling the algorithm to provide predictions quickly and precisely. In statistics, naive Bayes classifiers are thought

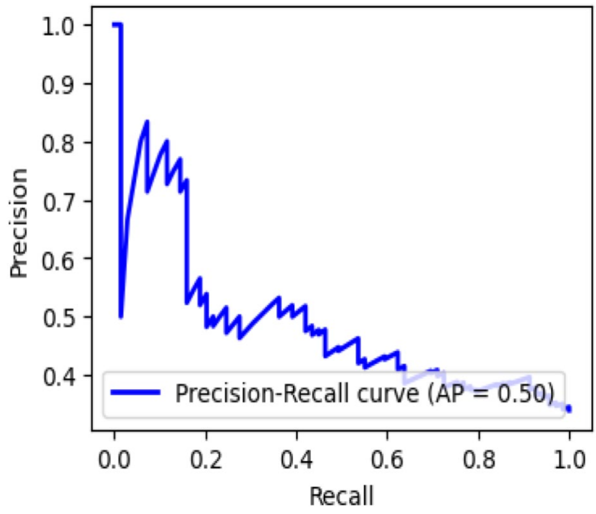

Fig. 8 Precision-Recall curve of Naïve Bayes

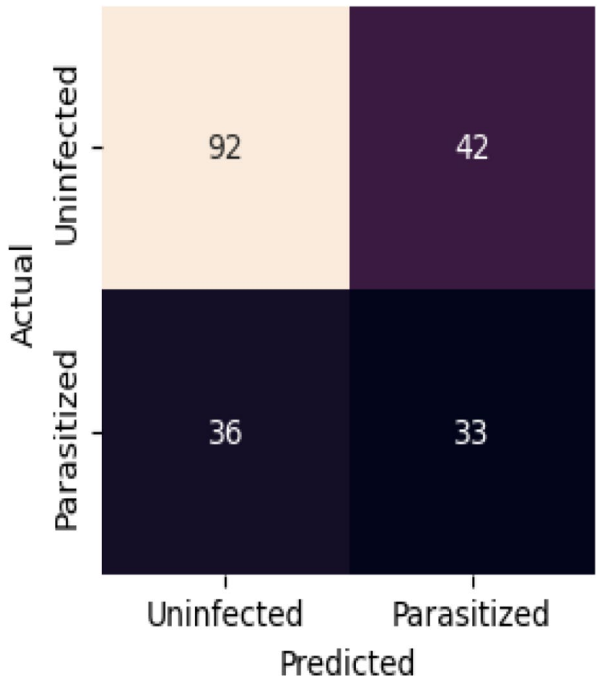

Fig. 9 Confusion matrix of Naïve Bayes method

of as simple probabilistic classifiers that use the Bayes theorem. The premise of this theorem is the likelihood of a hypothesis given the data and some prior knowledge. This is often not the case in real-world applications, as the naive Bayes classifier assumes that each feature in the input data is independent of every other feature. We have achieved 61% training accuracy, 62% testing accuracy, and an AUC score of 63% with our Naïve Bayes approach. Figure 8, depicts the Precision-Recall Curve

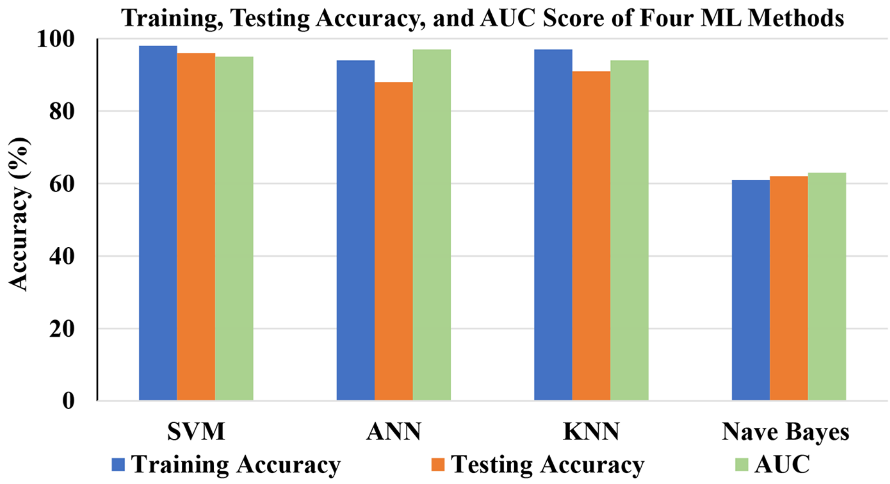

Fig. 10 Provides an extra graphical depiction of a comparison of the experimental findings of the proposed models

Table 1 Shows the summary model's performance in different metrics

Methods	Class	Precision (%)	Recall (%)	F1-score (%)	Training Accuracy (%)	Testing Accuracy (%)	AUC (%)
SVM	Uninfected	97	97	97	98	96	95
	Parasitized	95	95	95			
ANN	Uninfected	96	93	95	97	93	97
	Parasitized	88	93	90			
KNN	Uninfected	88	99	93	97	91	94
	Parasitized	98	74	84			
Naïve Bayes	Uninfected	72	69	70	61	62	63
	Parasitized	44	48	46			

of a Naïve Bayes model. The area under the Precision-Recall Curve (AP) is 50%, indicating that the system under evaluation has a modest overall performance. The Precision-Recall curve of this model is weak when compared to others. As depicted in Figs. 10 and 36 out of 69 patients who tested positive for malaria were incorrectly labeled as uninfected. In contrast to previous trials, Naïve Bayes performs worse.

5 Discussion

Our suggested IoT-based framework approach for malaria case detection, classification, and monitoring has been thoroughly validated utilizing data and performance assessment criteria. We used a variety of machine learning techniques, such as SVM, ANN, KNN, and Naïve Bayes. The results, as given in Fig. 10, and Table 1, indicate the model's training accuracy, testing accuracy, precision, recall, F1-score, and AUC score performance for identifying malaria illnesses. In comparison to prior trials, our proposed SVM technique has yielded encouraging results in correctly identifying whether particular malaria symptom data acquired from users indicated parasitized or normal conditions. This validation method strengthens our framework's efficacy in early detection and monitoring of malaria cases, giving a dependable tool for healthcare professionals and individuals to identify and handle probable malaria infections at an early stage. The results of our study demonstrate that a system for monitoring malaria in real-time, based on the Internet of Things and employing machine learning, outperforms recent studies. We have proposed a study that has exhibited improved accuracy and efficacy, as evidenced in Table 1, surpassing alternative methodologies. This suggests that our approach holds promise for effective monitoring and detection of malaria in real time. The use of IoT technology and machine learning algorithms has yielded significant advancements in the detection of malaria, thereby showing potential for enhancing healthcare outcomes and improving disease management. The findings underscore the potential advantages of combining IoT and machine learning in the healthcare sector, particularly in the context of monitoring and detecting infectious diseases. The real-time nature of the framework is particularly significant, especially in settings with a high burden of disease, where timely identification of malaria cases is of utmost importance. Immediate feedback on symptoms related to malaria aids healthcare providers in intervening promptly, potentially halting the spread of the disease. Continuous monitoring also provides a deeper understanding of the dynamics of malaria, enabling interventions to be tailored to individual patient needs and the progression of the disease. Our investigation has demonstrated to be significantly more precise and efficacious in the early identification and surveillance of malaria in comparison to prior investigations. By employing sophisticated techniques and conducting a thorough analysis, we have successfully identified malaria in its initial stages, well before it evolves into a severe and potentially fatal condition. This discovery facilitates prompt intervention and care, resulting in improved patient outcomes and reduced disease transmission.

Malaria is generally diagnosed by checking certain essential markers, such as the presence of the malarial parasite in blood smears, which are typically performed using thick or thin blood smear microscopy. Identification of specific signs and symptoms, such as fever, chills, headache, nausea, vomiting, and muscle pain, is critical. The presence of parasitized red blood cells, which can be detected by laboratory techniques such as polymerase chain reaction (PCR) and rapid diagnostic testing (RDT), is another important signal. Furthermore, machine learning and IoT technologies can evaluate real-time symptom data collected by wearable sensors to discover trends and forecast outcomes, so assisting in the early detection and classification of malaria cases as parasitic or normal. These technologies improve the accuracy and timeliness of malaria detection, hence improving patient outcomes and reducing the disease's impact.

The malaria early detection system, which combines machine learning and IoT technology, would integrate smoothly into existing healthcare workflows while delivering real-time monitoring and speedy diagnosis. This method can be implemented in clinics and hospitals, where IoT sensors continuously collect patient data and send it to machine learning models for fast analysis. Healthcare providers would receive real-time notifications and thorough reports on possible malaria cases, allowing them to start treatments on time and limit the risk of serious sequelae. The solution will reduce the strain on healthcare professionals by automating common diagnostic activities, freeing them up to focus on patient care and challenging cases. Additionally, the collected data will be centralized for improved disease tracking, public health strategies, patient outcomes, resource utilization, and healthcare infrastructure strengthening.

The proposed malaria detection system monitors a comprehensive set of fifteen critical symptoms during data collection. The symptoms are fever, chills, sweating, headache, nausea, vomiting, muscle pain, exhaustion, fast breathing, stomach discomfort, diarrhea, anemia, jaundice, convulsions, and altered consciousness. The study focuses on major malaria signs and symptoms, such as fever, chills, headaches, tiredness, vomiting, diarrhea, convulsions, anemia, jaundice, and hypoglycemia. The system can collect a wealth of information about the onset, length, and strength of these symptoms by monitoring them in real-time with wearable sensors and IoT devices. Machine learning algorithms will examine this data for patterns and correlations that suggest the existence of the malaria parasite. The ability to effectively connect these symptoms with malaria diagnosis enables the algorithm to distinguish malaria from other disorders with comparable symptoms, enhancing diagnostic accuracy.

Our investigation has the potential to revolutionize the identification and management of malaria, equipping healthcare providers with enhanced strategies to combat this global health concern. Our proposed study has shown better accuracy and effectiveness, as seen in Table 2, surpassing other methods. This indicates our approach has the potential for effective real-time malaria monitoring.

Our research on malaria detection utilizing IoT and machine learning has numerous limitations that should be considered. First, data quality and availability have a significant impact on machine learning model performance. Second, technological problems such as IoT infrastructure stability, connectivity issues, and sensor accuracy may have an impact on data gathering and real-time monitoring, thus limiting timely intervention. When collecting health data with IoT devices, ethical questions around data privacy, permission, and security must be carefully considered. Furthermore, incorporating new technology into existing healthcare systems necessitates overcoming institutional barriers such as compatibility with electronic health records, training healthcare workers, and procuring sufficient funding for deployment.

Table 2 Shows a comparison in light of recent studies in malaria detection

Authors	Methods	Dataset (records)	Precision (%)	Recall (%)	F1-score (%)	Training Accuracy (%)	Testing Accuracy (%)	AUC (%)
Meraj et al. [21]	ML, IoT	1000	68.3	--	--	67.4	68.3	--
Logesh et al. [22]	ML, IoT	1000	92.4	94.5	93.4	95.9	94.5	--
Sabukunze et al. [23]	ML, IoT	299	95	--	--	97.1	92.95	
Otoom et al. [24]	ML, IoT	14,251	--	--	93.0	--	92.95	--
Mehdi et al. [25]	ML, IoT	--	--	--	--	--	--	--
Our model	ML, IoT	1011	97	97	97	98	96	95

6 Conclusion and Future work

This study presented an IoT-based approach for mitigating the effects of malaria illnesses. The suggested framework was utilized to create a machine-learning-based prediction model for classifying the illness into parasitized or normal classes and to analyze treatment response using possible malaria case information and health records of confirmed malaria cases. This is particularly advantageous in the medical industry and users for making an early and exact diagnosis of malaria in patients using IoT wearable sensors and machine learning. Early diagnosis is critical in saving a person's life by guaranteeing effective and timely patient care. Through early identification of symptoms, the suggested real-time system might potentially lower the burden of malaria illnesses as well as fatality rates. Our study also will aid in the early detection of malaria to provide better healthcare services and avoid negative outcomes such as mortality. We observed the performance of SVM and other machine-learning methods. The SVM algorithm produced the greatest results across four experiments, with 98% training accuracy, 96% testing accuracy, and 95% AUC score. An interesting option for future research is the creation of hybrid machine learning models that combine the strengths of different techniques, such as SVM and Convolutional Neural Networks (CNNs), to improve malaria diagnosis accuracy. These hybrid models can better assess complicated, real-time data generated by IoT devices by combining the enhanced feature extraction skills of deep learning methods with the robust classification abilities of classic machine learning algorithms. Implementing edge computing can improve this system by processing data locally on IoT devices, lowering latency, and allowing for faster, real-time diagnostics. This merging of hybrid models with edge computing has the potential to transform malaria detection by providing rapid, accurate, and scalable solutions that can greatly enhance patient outcomes and streamline healthcare delivery.

Author Contributions A.M.A and W.S.A: Conceptualization, Methodology, Software, Writing review & editing original draft, Data curation, Methodology, Software. B.M.A, G.S.N, and Y.A.B: Visualization, Investigation, Visualization, Investigation, Validation.

Funding Authors declare no funding for this research.

Data Availability No datasets were generated or analysed during the current study.

Declarations

Competing Interests The authors declare no competing interests.

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