

Advancing Malaria Detection: A Comparative Study and Proposal for Web-Based Predictive Application Utilizing Convolutional Neural Network and TensorFlow

Egwu Samuel Onuche-Ojo1 , Eseyin Joseph B.2 , Dako Apaleokhai D.3 , Izuafa Braimah A.3

1Dept of Software Engineering, Veritas University Abuja, Abuja, Nigeria

2 ICT Directorate, University of Jos, Jos Nigeria

3Dept of Software Engineering, Veritas University Abuja, Nigeria

DOI: <https://doi.org/10.51584/IJRIAS.2024.906020>

Received: 14 May 2024; Revised: 31 May 2024; Accepted: 06 June 2024; Published: 05 July 2024

ABSTRACT

Malaria is a major public health problem in developing countries. The prevalence of malaria is increasing year by year, resulting in a decrease in the number of deaths and morbidity. Malaria has become a serious public health issue worldwide, particularly in low resource underserved rural communities. There is an urgent need for a web-based predictive application using TensorFlow and Convolutional Neural Networks (CNNs) for malaria detection. This paper provides a comparative overview of how the malaria situation has changed over time, showing which countries have maintained indigenous cases and which have progressed to different statuses by 2022. The goal of the paper is to showcase the efficacy of machine learning, particularly CNN and TensorFlow models, in detecting malaria using cell images. Moreover, the integration of a Web-Based Predictive System further enhances the accessibility and efficiency of our diagnostic tools, potentially contributing to better healthcare outcomes, especially in malaria-endemic regions.

Keyword: Malaria, TensorFlow, Convolutional Neural Networks (CNNs), Predictive application, Healthcare.

INTRODUCTION

Malaria continues to pose a significant global health challenge, particularly in countries like Nigeria (WHO, 2023). Despite ongoing efforts, the year 2022 saw a concerning increase in malaria cases worldwide, reaching an estimated 249 million—a marked rise from previous years (WHO, 2023). While progress had been made in reducing malaria incidences between 2000 and 2019, recent trends show a troubling reversal, with cases steadily increasing since 2015 (WHO, 2023). Nigeria, alongside countries such as Pakistan, Ethiopia, Uganda, and Papua New Guinea, bears a significant burden of this resurgence. Despite intensive control measures, Nigeria's malaria incidence has stabilized, largely due to rapid population growth. Conversely, other nations have experienced significant spikes in malaria incidence rates, highlighting the complex challenges in disease management and prevention (WHO, 2023).

Figure 1: Countries with indigenous cases in 2000 and their status by 2022. (WHO, 2023)

Figure 1 visually depicts the evolution of malaria endemicity status in countries from 2000 to 2022, specifically focusing on those with indigenous cases in 2000. It offers a comparative view of how the malaria situation has evolved over time, indicating which countries have maintained indigenous cases and which have transitioned to different statuses by 2022. This figure serves as a valuable tool for understanding the dynamic nature of malaria transmission and control efforts globally.

Moreover, malaria presents a range of debilitating symptoms, from fever and chills to headaches and general discomfort, with severe complications such as seizures and mortality looming if untreated (Hemachandran et al., 2023). Early diagnosis and treatment are essential in mitigating these outcomes, often requiring the detection of the parasite in the patient's blood through various diagnostic methods, including microscopy and rapid tests. While microscopy is considered the gold standard, rapid diagnostic tests have become popular, although concerns persist regarding false negatives, particularly in endemic areas due to gene deletions in the parasite's genome (Hemachandran et al., 2023).

Despite numerous studies exploring different aspects of malaria prediction systems, none have extensively addressed the development of a web-based malaria predictive system to offer accurate forecasts of malaria outbreaks in real-time, empowering healthcare professionals and policymakers with actionable insights. This study aims to bridge this gap by leveraging advanced machine learning techniques, particularly Convolutional Neural Networks (CNNs) and TensorFlow, to enhance the prediction accuracy of malaria outbreaks.

The selection of CNNs and TensorFlow is driven by their proven efficacy in handling large datasets and complex pattern recognition tasks. CNNs are particularly adept at image recognition and classification, which is essential for diagnosing malaria through blood smear images. TensorFlow, an open-source machine learning framework, offers robust tools for building and training deep learning models, making it a suitable choice for developing a scalable and efficient predictive system.

The data utilized in this study includes both textual and image data. Textual data comprises historical records of malaria cases, weather patterns, and demographic information, while image data includes blood smear images used for parasite detection. By integrating these diverse data forms, the predictive system

aims to provide comprehensive and accurate forecasts.

The subsequent sections of the paper are organized as follows: Section 2 provides a literature review, offering an overview of existing research on malaria prediction models and examining methodologies, data sources, and challenges. It also explores the role of machine learning and deep learning techniques, such as TensorFlow and CNN, in malaria prediction. Section 3 outlines the methodology, while Section 4 presents the results and analysis. Finally, Section 5 offers concluding remarks from the study and Section 6 discusses future avenues of research.

LITERATURE REVIEW

The literature review provides a comprehensive exploration of the application of Machine Learning (ML) and its modern counterpart, deep learning models, within healthcare settings. ML applications in healthcare offer valuable insights into individual patient treatment experiences, medication options, and the effects of new drugs. Researchers have increasingly turned to ML methods to detect various diseases, such as diabetes, stroke, cancer, malaria, and heart disease, recognizing their potential to revolutionize healthcare outcomes. Here, we delve into some of these methods, drawn from the most commonly employed algorithms in the healthcare domain (De Oliveira et al., 2018; S. S. Yadav et al., 2021).

Decision Tree (DT) emerges as a notable supervised classifier, known for its simplicity and interpretability. Constructed by recursively partitioning a labeled set of observations, DT classifiers find applications in diverse clinical scenarios, including dermatological treatment efficacy enhancement, critical hypertension estimation, and cardiac arrhythmia detection and classification (Mehrpour et al., 2023; S. S. Yadav et al., 2021). The data used in these studies often include patient medical records, clinical measurements, and diagnostic test results, facilitating the training of decision tree models on structured, labeled datasets.

Random Forest (RF), an ensemble learning approach constructed from multiple decision tree classifiers, offers enhanced predictive performance through aggregation. Sharing similar hyperparameters with DT, RF classifiers contribute to disease detection and prognosis in various medical contexts (Minnoor & Baths, 2022). In RF applications, the datasets typically comprise a wide range of medical data, including demographic information, clinical features, and outcomes, enabling robust prediction and classification through the ensemble method.

Naive Bayes (NB), a supervised machine learning algorithm, operates on the principle of Bayes' theorem, assuming independence between features. Widely employed in medical applications, NB classifiers aid in heart disease diagnosis, psychiatric emergencies, and other clinical settings (Saleh et al., 2023; Kaviani & Dhotre, 2017). These studies often use datasets containing categorical and numerical variables representing patient symptoms, diagnostic test results, and treatment outcomes to model the probabilistic relationships between features.

Logistic Regression (LR), specializing in binary classifications, calculates the probability of a particular class label based on contextual or ordinary explanatory variables. In healthcare, LR is utilized for malaria prediction and identifying at-risk populations in public health research and outreach (Wu et al., 2023). Data used in LR studies frequently include binary outcome variables, such as disease presence or absence, and predictor variables related to patient demographics, environmental factors, and clinical measurements.

Support Vector Machine (SVM) Classification delineates data input with a hyperplane to establish an optimal decision boundary, contributing to improved patient management and outcomes, particularly in diagnosing conditions like coronary artery disease (Sahu et al., 2023). The datasets for SVM applications generally include high-dimensional medical data, with features derived from imaging, genetic information, and comprehensive clinical records.

Artificial Neural Network (ANN), simulating biological neural networks, excels in pattern recognition tasks, facilitating disease diagnosis and risk assessment in healthcare settings (Mehlig, 2021). ANN models are trained on large datasets encompassing varied forms of medical data, such as imaging data, time-series data from wearable sensors, and electronic health records, to capture complex patterns and correlations.

Recent advancements in computer-aided diagnosis offer promising avenues for improving malaria detection through automated image analysis. Convolutional Neural Network (CNN)-based models demonstrate remarkable effectiveness in malaria diagnosis, with various techniques, such as data augmentation and feature extraction, enhancing diagnostic accuracy (Hemachandran et al., 2023; Thakur et al., 2023). The datasets used in these studies primarily consist of microscopic images of blood samples, where CNNs are applied to detect malaria-infected cells with high precision.

Moreover, Bayesian decision networks (BDNs) and generalized linear models (GLMs) have shown efficacy in malaria prediction, with BDNs offering superior predictive performance and flexibility compared to traditional methods (Militante, 2019). These models utilize diverse datasets, including epidemiological data, climate variables, and historical malaria incidence rates, to forecast disease outbreaks and inform public health strategies.

Ensemble methods and innovative approaches, including DNA-based sensors and fiber sensors, show promise in malaria diagnosis, albeit challenges persist in accurately identifying malaria infection, especially in high transmission rate areas (Reboud et al., 2019). Recent studies explore machine learning approaches, including random forest models and CNN architectures, for malaria diagnosis, showcasing high accuracy rates in regional-specific prediction models (Mariki et al., 2022; Marques et al., 2022). These studies leverage extensive datasets, combining genetic data, environmental factors, and clinical findings to enhance the predictive accuracy and generalizability of the models.

Figure 2: A flowchart of feature selection heuristic in malaria prediction system. (Militante, 2019).

Figure 2 shows the flow chart of how convolutional layers and pooling layers work to predict cells detected with malaria.

The primary focus of this research is to address the urgent need for a web-based predictive application for

malaria detection, utilizing TensorFlow and Convolutional Neural Networks (CNN).

The dataset, consisting of 27,558 cell images for malaria detection, was obtained from Kaggle, comprising 13,779 parasitized and 13,779 uninfected cell images (Militante, 2019), This research distinguishes itself from Militante's work by not only employing CNNs and similar datasets but also integrating TensorFlow to enhance computational efficiency and scalability. While Militante's research highlights the efficacy of CNNs in malaria prediction, our study emphasizes the development of a comprehensive, accessible webbased system that can be readily deployed in various healthcare settings. This approach aims to improve model performance, ensure robust validation, and ultimately contribute to more accurate and timely malaria diagnosis and intervention.

In conclusion, the literature review underscores the urgent need for a web-based predictive application utilizing TensorFlow and CNN for malaria detection. While traditional methods have laid the groundwork, integrating deep learning techniques holds promise for improving accuracy. Challenges remain, including computational efficiency and data heterogeneity. Interdisciplinary collaboration and innovative research methodologies will be crucial for advancing malaria prediction and enhancing public health outcomes.

METHODOLOGY

3.1.1 Overview of the Proposed Approach

To enhance public health through a web-based malaria prediction system, we adopt a combined approach utilizing both the machine learning development life cycle and the software development life cycle for the web application. The methodology comprises several stages, including data collection, preprocessing, exploratory data analysis (EDA), model development, web application development, evaluation, deployment, and impact assessment (Militante, 2019).

3.1.2 Data Collection

The dataset, consisting of 27,558 cell images for malaria detection, was obtained from Kaggle, comprising 13,779 parasitized and 13,779 uninfected cell images (Militante, 2019). Unlike Militante's research, which primarily focuses on utilizing CNN for malaria detection with this dataset, our research aims to develop a web-based predictive application using TensorFlow and CNN. This application not only enhances diagnostic accuracy but also addresses challenges related to computational efficiency and data heterogeneity, providing a more robust and accessible solution for malaria detection.

3.1.3 Data Preprocessing

1. Import Libraries: Necessary libraries for data manipulation and visualization, including image processing and machine learning, will be imported (Militante, 2019).

2. Read Images: Images from directories for both parasitized and uninfected cells will be read into thesystem (Militante, 2019).

3. Data Integrity Check: Verification of the total number of entries in each directory to ensure dataset integrity and consistency (Militante, 2019).

3.1.4 Exploratory Data Analysis (EDA)

1. Visualize Samples: Random samples of 25 parasitized and uninfected cell images will be visualized to observe distinctive features and variations (Patel et al., 2022).

2. Examine Characteristics: Individual cell images will be examined to identify malaria infection characteristics, such as the presence of purple spots or irregular shapes.

3. Dimension Analysis: Joint plots will be generated to analyze the distribution of dimensions (width and height) for both parasitized and uninfected cell images, providing insights into potential feature engineering strategies (Patel et al., 2022).

3.1.5 Model Development

1. Feature Extraction: Meaningful features will be extracted from the cell images using techniques such as convolutional neural networks (CNNs) and TensorFlow (Thieme et al., 2020).

2. Model Training: Machine learning models, such as CNNs or other classifiers, will be trained on the preprocessed image data to predict malaria infection (Thieme et al., 2020).

3. Model Optimization: Model hyperparameters and architectures will be optimized through techniques like grid search or random search to improve prediction performance (Thieme et al., 2020).

3.1.6 Web Application Development

1. Frontend Design: The user interface of the web application will be designed for intuitive interaction, incorporating features for image upload and prediction display (R. Yadav et al., 2021).

2. Backend Implementation: The backend functionality of the web application, including model integration, image processing, and result visualization, will be developed (R. Yadav et al., 2021).

3.1.7 Evaluation

1. Performance Metrics: Model performance will be evaluated using standard metrics such as accuracy, precision, recall, and F1-score (Whalen et al., 2022).

2. User Experience Testing: Usability testing will be conducted to assess the user experience and interface design of the web application (Whalen et al., 2022).

2. Cross-Validation: Cross-validation techniques will be applied to assess the generalization performance of the model on unseen data (Whalen et al., 2022).

3.1.8 Deployment and Impact Assessment

1. Web Application Deployment: The web-based malaria prediction system will be deployed on a suitable platform, ensuring scalability and availability (R. Yadav et al., 2021).

2. Real-World Testing: Validation of the prediction system will be conducted in real-world settings, collaborating with healthcare institutions and stakeholders (Whalen et al., 2022).

3. Impact Assessment: The impact of the prediction system on public health outcomes, including malaria incidence reduction and resource allocation optimization, will be assessed (Whalen et al., 2022).

In summary, the methodology combines machine learning and software development methodologies to create a web-based malaria prediction system. Through data collection, model development, and web

application design, the aim is to provide an effective tool for malaria detection and contribute to public health improvement efforts.

RESULTS & ANALYSIS

The study's findings underscore the effectiveness of machine learning models, particularly CNN, in malaria detection using cell images. Exploratory data analysis (EDA) revealed distinct features in parasitized and uninfected cell images, with parasitized cells displaying characteristic purple spots indicative of malaria infection. The dataset, consisting of 27,558 images evenly distributed between parasitized and uninfected categories, provided a robust foundation for model development.

Following data preprocessing, the models were trained and evaluated, including CNN. The results showed promising performance metrics, with an accuracy of 0.9717, indicating the model's capability in accurate malaria detection.

Additionally, a web-based predictive system was developed to leverage the trained machine learning models for real-time malaria detection. This platform offers accessible and efficient diagnostic tools, contributing significantly to improved healthcare outcomes in malaria-endemic regions.

Table 1: Classification report of the model

The table below shows the classification report of the model used to predict cells detected with malaria. It shows that the model is accurate and can be utilized to predict cells detected with malaria in future cases.

Figure 3: Malaria Detection Home page.

The interface depicted in Figure 3 allows for the uploading of cells suitable for detection purposes.

Figure 4: Result page.

Figure 4 displays the malaria-infected cells along with their respective detection percentages.

The study demonstrates the potential of machine learning models in malaria detection using cell images. Through comprehensive data analysis and model development. The integration of a web-based predictive system further enhances the accessibility and usability of our diagnostic tools, facilitating timely and effective malaria diagnosis.

Moving forward, continued research and validation studies are essential to further refine and optimize our models for real-world applications. By harnessing the power of machine learning and web-based technologies, we can make significant strides in combatting malaria and improving healthcare outcomes worldwide.

CONCLUSION

The research showcased the efficacy of machine learning, particularly CNN and Tensorflow models, in detecting malaria using cell images. With a dataset of 27,558 evenly distributed images between parasitized and uninfected categories, the models were trained and evaluated, achieving an impressive accuracy of 0.9717. The exploration through exploratory data analysis highlighted distinct features in parasitized and uninfected cells, aiding in model development. (Militante, 2019)

Additionally, the development of a web-based predictive system enhances the accessibility and efficiency of malaria diagnosis, potentially contributing to better healthcare outcomes, particularly in malaria-endemic regions. The system allows real-time detection of malaria-infected cells, providing a user-friendly interface for uploading and viewing results. (R. Yadav et al., 2021)

The classification report of the model further supports its accuracy and reliability in predicting malariainfected cells. Such robust performance underscores the potential of machine learning models in medical diagnostics, paving the way for improved disease detection and management. (Sahu et al., 2023)

Looking ahead, the study emphasizes the importance of continued research and validation to refine and

optimize the models for real-world applications. By leveraging machine learning and web-based technologies, there's a promising avenue for advancing malaria detection and ultimately enhancing global healthcare efforts. (S. S. Yadav et al., 2021)

RESEARCH DIRECTIONS

Over the past decade, healthcare diagnosis has witnessed remarkable progress, with significant advancements in various research directions. Here, five important themes that highlight future directions in healthcare diagnosis are briefly discussed:

1. Enhanced Model Performance and Generalization:

Investigating techniques to further enhance the performance and generalization capabilities of machine learning models for malaria detection. This could involve exploring advanced CNN architectures, optimization algorithms, or ensemble methods to improve model robustness across diverse datasets and environmental conditions (Begum et al., 2024).

2. Interpretability and Explainability:

The focus is on developing interpretable machine learning models for malaria detection to foster trust and understanding among healthcare practitioners and end-users. Research efforts could delve into methods for extracting meaningful features from cell images and providing insights into the decision-making process of the models (Kasula, 2024).

3. Real-time Deployment and Integration:

Strategies are explored for seamlessly integrating machine learning-based diagnostic tools into existing healthcare infrastructure, especially in resource-constrained settings. This may involve optimizing model inference speed, designing user-friendly interfaces, and addressing data privacy and security concerns (Corbin et al., 2023).

4. Transfer Learning and Domain Adaptation:

The investigation focuses on the efficacy of transfer learning and domain adaptation techniques for malaria detection across different populations, geographical regions, and imaging modalities. Research in this area could explore methods to leverage pre-trained models on related tasks or datasets to improve model performance in new contexts with limited labeled data (Cheng et al., 2023).

5. Multimodal Fusion and Clinical Decision Support:

Exploration involves the integration of multiple data modalities, such as cell images, patient demographics, and clinical history, to develop comprehensive clinical decision support systems for malaria diagnosis and treatment. Research efforts in this domain could focus on multimodal fusion techniques, predictive modeling, and risk stratification to provide personalized healthcare recommendations (Cui et al., 2024).

These research directions aim to advance the field of machine learning in malaria detection while addressing critical challenges related to model performance, interpretability, deployment, adaptation, and clinical utility. By tackling these themes, researchers can contribute to improving the accessibility, accuracy, and effectiveness of malaria diagnosis, ultimately leading to better healthcare outcomes worldwide.

REFERENCES

- 1. Begum, M., Shuvo, M. H., Nasir, M. K., Hossain, A., Hossain, M. J., Ashraf, I., Uddin, J., & Samad, M. A. (2024). LCNN: Lightweight CNN architecture for software defect feature identification using Explainable AI. *IEEE Access*, *12*(January), 55744–55756. https://doi.org/10.1109/ACCESS.2024.3388489
- 2. Cheng, H., Kong, X., Wang, Q., Ma, H., Yang, S., & Chen, G. (2023). Deep transfer learning based on dynamic domain adaptation for remaining useful life prediction under different working conditions. *Journal of Intelligent Manufacturing*, *34*(2), 587–613. https://doi.org/10.1007/s10845-021- 01814-y
- 3. Corbin, C. K., Maclay, R., Acharya, A., Mony, S., Punnathanam, S., Thapa, R., Kotecha, N., Shah, N. H., & Chen, J. H. (2023). DEPLOYR: A technical framework for deploying custom real-time machine learning models into the electronic medical record. *Journal of the American Medical Informatics Association*, *30*(9), 1532–1542. https://doi.org/10.1093/jamia/ocad114
- 4. Cui, S., Wang, J., Zhong, Y., Liu, H., Wang, T., & Ma, F. (2024). Automated Fusion of Multimodal Electronic Health Records for Better Medical Predictions. *Proceedings of the 2024 SIAM International Conference on Data Mining (SDM)*, 361–369. https://doi.org/10.1137/1.9781611978032.41
- 5. De Oliveira, H., Prodel, M., & Augusto, V. (2018). Binary Classification on French Hospital Data: Benchmark of 7 Machine Learning Algorithms. *Proceedings – 2018 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2018*, 1743–1748. https://doi.org/10.1109/SMC.2018.00301
- 6. Hemachandran, K., Alasiry, A., Marzougui, M., Ganie, S. M., Pise, A. A., Alouane, M. T. H., & Chola, C. (2023). Performance Analysis of Deep Learning Algorithms in Diagnosis of Malaria Disease. *Diagnostics*, *13*(3). https://doi.org/10.3390/diagnostics13030534
- 7. Kasula, B. Y. (2024). Advancements in AI-driven Healthcare: A Comprehensive Review of Diagnostics, Treatment, and Patient Care Integration. *International Journal of Machine Learning for Sustainable Development*, *1*(1), 1–5.
- 8. Kaviani, P., & Dhotre, S. (2017). International Journal of Advance Engineering and Research Short Survey on Naive Bayes Algorithm. *International Journal of Advance Engineering and Research Development*, *4*(11), 607–611.
- 9. Mariki, M., Mkoba, E., & Mduma, N. (2022). Combining Clinical Symptoms and Patient Features for Malaria Diagnosis: Machine Learning Approach. *Applied Artificial Intelligence*, *36*(1). https://doi.org/10.1080/08839514.2022.2031826
- 10. Marques, G., Ferreras, A., & de la Torre-Diez, I. (2022). An ensemble-based approach for automated medical diagnosis of malaria using EfficientNet. *Multimedia Tools and Applications*, *81*(19), 28061– 28078. https://doi.org/10.1007/s11042-022-12624-6
- *11.* Mehlig, B. (2021). Machine Learning with Neural Networks. *Machine Learning with Neural Networks* . https://doi.org/10.1017/9781108860604
- 12. Mehrpour, O., Saeedi, F., Vohra, V., Abdollahi, J., Shirazi, F. M., & Goss, F. (2023). The role of decision tree and machine learning models for outcome prediction of bupropion exposure: A nationwide analysis of more than 14 000 patients in the United States. *Basic and Clinical Pharmacology and Toxicology*, *133*(1), 98–110. https://doi.org/10.1111/bcpt.13865
- 13. Militante, S. V. (2019). Malaria Disease Recognition through Adaptive Deep Learning Models of Convolutional Neural Network. *ICETAS 2019 – 2019 6th IEEE International Conference on Engineering, Technologies and Applied Sciences*, *07*(15), 6662–6672. https://doi.org/10.1109/ICETAS48360.2019.9117446
- 14. Minnoor, M., & Baths, V. (2022). Diagnosis of Breast Cancer Using Random Forests. *Procedia Computer Science*, *218*(2022), 429–437. https://doi.org/10.1016/j.procs.2023.01.025
- 15. Patel, H., Guttula, S., Mittal, R. S., Manwani, N., Berti-Equille, L., & Manatkar, A. (2022). Advances in Exploratory Data Analysis, Visualisation and Quality for Data Centric AI Systems. In *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (Vol. 1,

Issue 1). Association for Computing Machinery. https://doi.org/10.1145/3534678.3542604

- 16. Reboud, J., Xu, G., Garrett, A., Adriko, M., Yang, Z., Tukahebwa, E. M., Rowell, C., & Cooper, J. M. (2019). Paper-based microfluidics for DNA diagnostics of malaria in low resource underserved rural communities. *Proceedings of the National Academy of Sciences of the United States of America*, *116* (11), 4834–4842. https://doi.org/10.1073/pnas.1812296116
- 17. Roy, A., & Chakraborty, S. (2023). Support vector machine in structural reliability analysis: A review. *Reliability Engineering & System Safety*, *233*(April), 109126. https://doi.org/10.1016/j.ress.2023.109126
- 18. Sahu, P., Priyadarshini, P., Tripathy, S., Das, Y., Pradhan, S., & Sahu, K. (2023). *Machine Learning Strategies for Malaria Risk Prediction based on Text-based Clinical Information*. https://doi.org/10.21203/rs.3.rs-2938711/v1
- 19. Saleh, A., Dharshinni, N. P., Perangin-angin, D., Azmi, F., & Sarif, M. I. (2023). *Implementation of Recommendation Systems in Determining Learning Strategies Using the Naïve Bayes Classifier Algorithm*. *7*(1), 256–267.
- 20. Thakur, P. S., Sheorey, T., & Ojha, A. (2023). VGG-ICNN: A Lightweight CNN model for crop disease identification. *Multimedia Tools and Applications*, *82*(1), 497–520. https://doi.org/10.1007/s11042-022-13144-z
- 21. Thieme, A., Belgrave, D., & Doherty, G. (2020). Machine Learning in Mental Health: A systematic review of the HCI literature to support the development of effective and implementable ML Systems. *ACM Transactions on Computer-Human Interaction*, *27*(5). https://doi.org/10.1145/3398069
- 22. Whalen, S., Schreiber, J., Noble, W. S., & Pollard, K. S. (2022). Navigating the pitfalls of applying machine learning in genomics. *Nature Reviews Genetics*, *23*(3), 169–181. https://doi.org/10.1038/s41576-021-00434-9
- 23. WHO. (2023). *World malaria World malaria report report*. [https://www.wipo.int/amc/en/mediation/%0Ahttps://www.who.int/teams/global-malaria](http://www.who.int/teams/global-malaria-)programme/reports/world-malaria-report-2023
- 24. Wu, T. T., Wei, Y. Q., Wu, J. B., Yi, B. L., & Li, H. (2023). Logistic regression technique is comparable to complex machine learning algorithms in predicting cognitive impairment related to post intensive care syndrome. *Scientific Reports*, *13*(1), 1–15. https://doi.org/10.1038/s41598-023- 28421-6
- 25. Yadav, R., Yadav, R., & Gupta, S. B. (2021). Comparative Study of various Stable and Unstable sorting Algorithms. In *Artificial Intelligence and Speech Technology*. https://doi.org/10.1201/9781003150664-51
- 26. Yadav, S. S., Kadam, V. J., Jadhav, S. M., Jagtap, S., & Pathak, P. R. (2021). Machine learning based malaria prediction using clinical findings. *2021 International Conference on Emerging Smart Computing and Informatics, ESCI 2021*, *April*, 216–222. https://doi.org/10.1109/ESCI50559.2021.9396850