



## Al, Machine Learning, and the Fight Against Malaria

Presenter: Dr. Edna C. Too

Senior Lecturer, Computer Sciences Department, Chuka University

#### Dr. Edna Chebet Too: Al Researcher Profile

#### Senior Lecturer & Al Researcher

- PhD in Computer Science from Beijing University of Technology (BJUT), Beijing, China
- Renowned expert in advanced deep learning architectures (CNN, UNet) with multiple published papers
- Groundbreaking research on AI applications in healthcare diagnostics (TB and Breast cancer) and precision agriculture (pest and disease diagnosis)

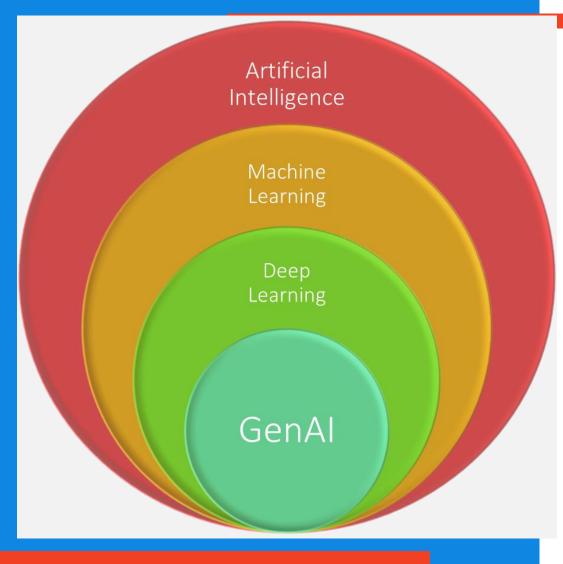
Senior Research Analyst at the Centre for Data Analysis & Modeling (CDAM), where she directs interdisciplinary Al initiatives and mentors emerging researchers

# The Malaria Challenge

- Malaria remains one of the world's most persistent public health challenges:
  - 247 million cases globally in 2021
  - 619,000 deaths annually
  - 95% of cases concentrated in 29 countries
  - Children under 5 account for 80% of deaths in Africa
  - Estimated economic impact of \$12 billion annually
  - Traditional surveillance and control methods are resource-intensive and often reactive rather than proactive.



### Al vs. Machine Learning: The Big Picture



- Artificial Intelligence (AI) is a branch of computer science that deals with creating intelligent agents, which are systems that can reason, learn, and act autonomously.
- Machine Learning-subset of AI that focuses on developing algorithms and models that allow computers to learn from data and improve their performance over time
- Deep Learning-a subset of machine learning that focuses on using artificial neural networks with multiple layers to learn complex patterns and representations from data. These neural networks are inspired by the structure and function of the human brain, with interconnected nodes (neurons) that process information in layers.
- All aims to build machines that can think and behave like humans.



# How Machines Learn: The "Aha!" Moment

#### MACHINE LEARNING TECHNIQUES





#### **Supervised Learning**

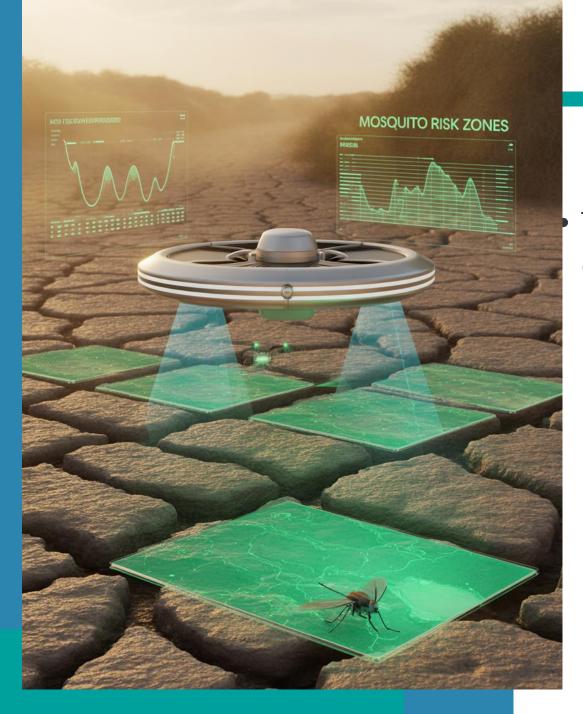
- Machines learn from labeled examples
- Example: An algorithm identifies cat images after training on thousands of photos labeled "cat" or "not cat"
- Like learning with a teacher who provides answers

#### **Unsupervised Learning**

- Machines discover hidden patterns in unlabeled data
- Example: Grouping customers by purchasing behavior without predefined categories
- Like finding structure without guidance

#### **Reinforcement Learning**

- Machines learn through trialand-error with rewards/penalties
- Example: AlphaGo mastering the game of Go through millions of self-played games
- Like learning to ride a bike through practice

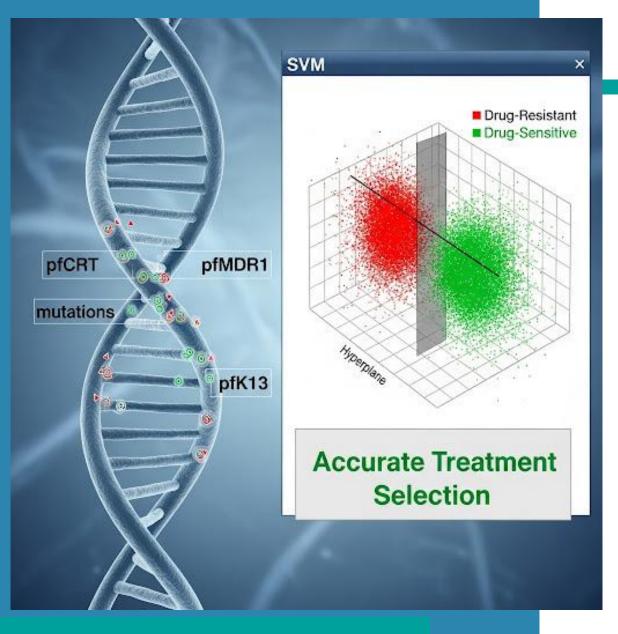


# Forests for Transmission Hotspot Identification

iviaciiiie Leai iiiig.ivai iuoiii

These ensemble models aggregate diverse data sources including:

- Climate factors (temperature variations, rainfall patterns, humidity levels)
- Land use data (vegetation indices from satellite imagery, water body detection)
- Socioeconomic indicators (population density, housing quality, healthcare access)



# Support Vector Machines for Drug Resistance Prediction

- SVMs analyze parasite genomic sequences, particularly mutations in:
- Used to analyze malaria parasite genomic mutations in key resistance genes:
  - Chloroquine resistance
  - Multi-drug resistance
- Impact:

Supports accurate treatment selection and real-time monitoring of resistance patterns.

# Temporal Data: Al 29% 🔓 20% 🕏 🗗 40% Intervention Coverage Metrics Prediction: Up to 4 Weeks in Advance Spatial Data: Population Density & Movement

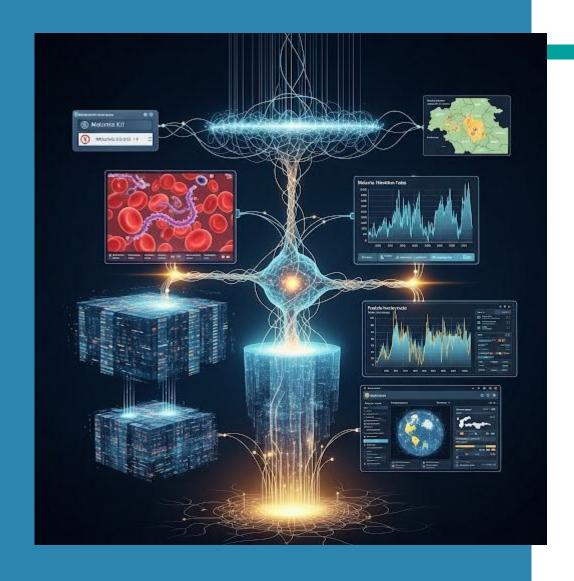
# (XGBoost) for Outbreak Forecasting

- Integrates temporal and spatial features:
  - Historical incidence rates with seasonal patterns
  - Population density and movement data
  - Intervention coverage metrics (bed nets, indoor spraying, treatment access)
- Accurate prediction of malaria surges up to 4 weeks in advance, enabling proactive resource allocation



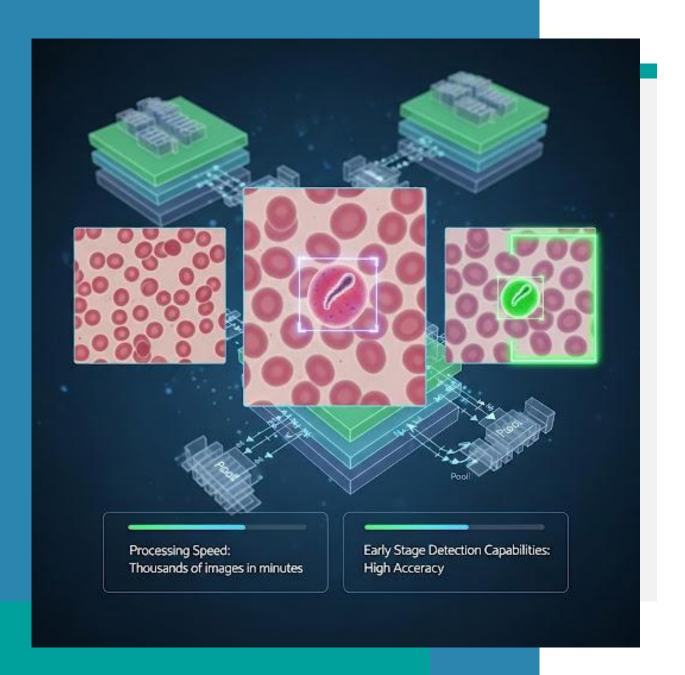
### **Clustering & Regression**

- This unsupervised learning approach groups communities by similar epidemiological profiles, revealing distinct "malaria ecotypes" that require tailored intervention strategies:
  - High vs. low transmission intensity clusters
  - Seasonal vs. perennial transmission patterns
  - Urban vs. rural transmission dynamics



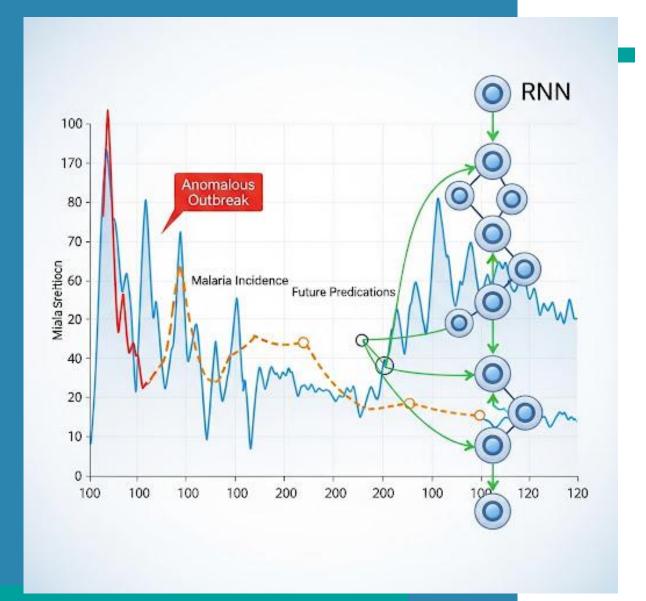
# Deep Learning's Visionary Breakthroughs

- Deep learning approaches have revolutionized malaria research by extracting insights from complex, unstructured data that traditional methods cannot process.
- These sophisticated neural network architectures excel at image recognition, time series analysis, and pattern detection across massive datasets, opening new frontiers in malaria surveillance, diagnosis, and prediction.



## Convolutional Neural Networks (CNNs)

- These vision-based networks analyze microscopic blood smear images with remarkable efficiency:
- identifying *P. falciparum* and *P. vivax* parasites
- Process thousands of images in minutes versus hours of manual microscopy
- Detect parasites at earlier stages and lower densities than human technicians



### Recurrent Neural Networks (RNNs/LSTMs)

- These sequential models excel at temporal pattern recognition:
- Predict malaria incidence trends weeks to months in advance
- Capture complex seasonal patterns and multiyear cycles
- Detect anomalous outbreaks against expected background rates

## Synthetic Real or Random GAN fake-fake Synthetic Probablity Discriminator Generator noise

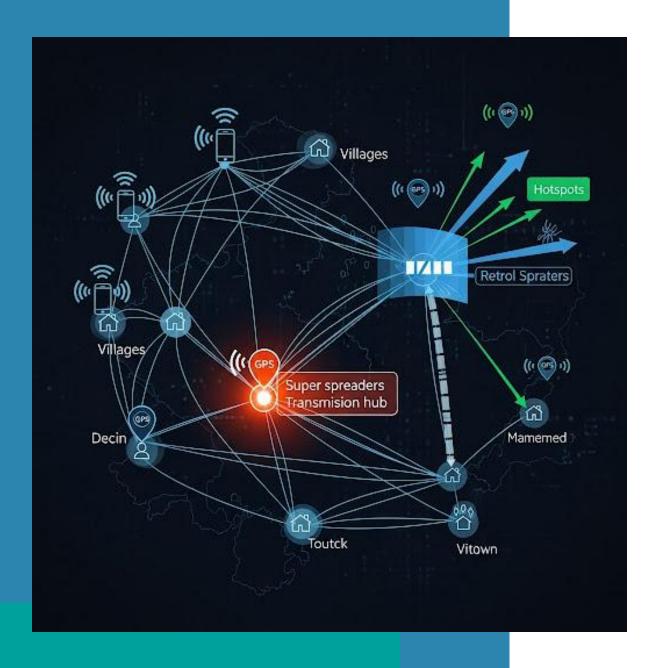
# Generative Adversarial Networks (GANs)

- These generative models address critical data limitations:
  - Create synthetic but realistic blood smear images for training
  - Generate examples of rare parasite morphologies and atypical presentations
  - Improve model robustness through diverse training examples



### Geospatial Deep Learning: U-Net Architecture

- This specialized image segmentation network:
  - Processes high-resolution satellite imagery to identify potential breeding sites
  - Precisely delineates water bodies, agricultural fields, and other habitats
  - Guides targeted larvicide application with meter-level precision
  - Monitors environmental changes that impact vector populations



# Graph Neural Networks (GNNs) for Transmission Networks

- These advanced networks model complex relationships between nodes (people, locations) and edges (movements, interactions):
  - Incorporate mobile phone data to track population movement patterns
  - Identify key "super-spreader" individuals or critical transmission hubs
  - Model how interventions at specific nodes impact overall transmission
  - Predict how parasite strains spread through human networks
  - GNNs reveal the social dimension of malaria transmission, crucial for breaking infection chains in highly mobile populations.



## AI: A New Weapon in the Fight

#### Transforming the Approach

Al fundamentally changes how we combat malaria:

- ☐ Processes massive, complex datasets from diverse sources (climate, population, case reports, satellite imagery)
- ☐ Shifts strategy from **reactive** crisis management to **proactive**, data-driven prevention
- ☐ Accelerates every phase: from understanding disease dynamics to deploying limited resources effectively
- ☐ Enables precision targeting of interventions where and when they'll have maximum impact

#### **Mosquito Surveillance & Detection**



#### Image Recognition for Species Identification

Convolutional Neural Networks (CNNs) classify mosquito species from photographs, significantly outperforming traditional methods requiring expert entomologists.



#### **Drone-Based Monitoring**

Al-powered UAVs with multispectral imaging identify breeding sites by detecting water bodies and vegetation patterns associated with mosquito habitats.



#### **Acoustic Recognition**

Deep learning models analyze wingbeat frequencies (500-700 Hz for Anopheles) through smartphone microphones, enabling citizen science participation in surveillance.



#### **Smart Traps**

IoT-enabled traps count, identify, and report mosquito captures in real-time. Systems like Microsoft's Project Premonition autonomously collect specimens for genomic analysis.

**Mosquito Surveillance & Detection** 



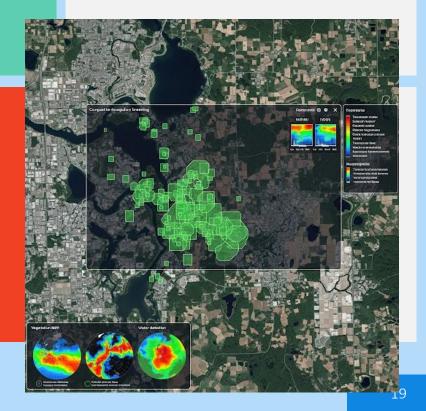


#### Mobile Applications

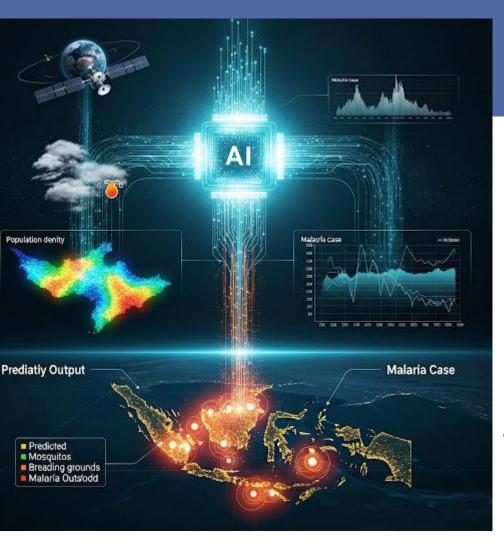
Citizen science apps empower communities to report mosquito sightings, using AI for identification, building vast and cost-effective surveillance networks.

#### Remote Sensing

Satellite imagery combined with computer vision algorithms analyzes vast geographic areas to pinpoint environmental conditions favoring mosquito breeding.



### **Predictive Power: Forecasting Outbreaks**



• AI models analyze:

#### **Data Inputs**

- Climate data (temperature, rainfall patterns)
- Population density and movement
- Historical case data
- Mosquito breeding conditions

#### **Al Processing**

- Machine learning algorithms:
  - Identify complex correlations humans would miss
  - Learn from previous outbreak patterns
  - Generate probability models

#### **Outbreak Prediction**

- Results show:
  - Predicting outbreaks weeks or months in advance



### **Predictive Malaria Risk Mapping**

ML algorithms integrate multiple data sources to create high-resolution risk maps:

- Environmental data: Temperature, rainfall, humidity, elevation, vegetation index
- Land use patterns: Agricultural practices, urbanization, deforestation
- Socioeconomic factors: Population density, housing quality, access to healthcare
- Historical case data: Temporal and spatial distribution of previous outbreaks
- Models achieve 80-90% accuracy in predicting high-risk zones at 1km<sup>2</sup> resolution, enabling targeted intervention deployment.

Commonly used algorithms include Random Forest, Gradient Boosting Machines, and Deep Neural Networks with geospatial components.



### **Early Warning Systems**

#### Data Integration

Continuous collection of climate data, case reports, vector surveillance, and population movement patterns.

#### ML Processing

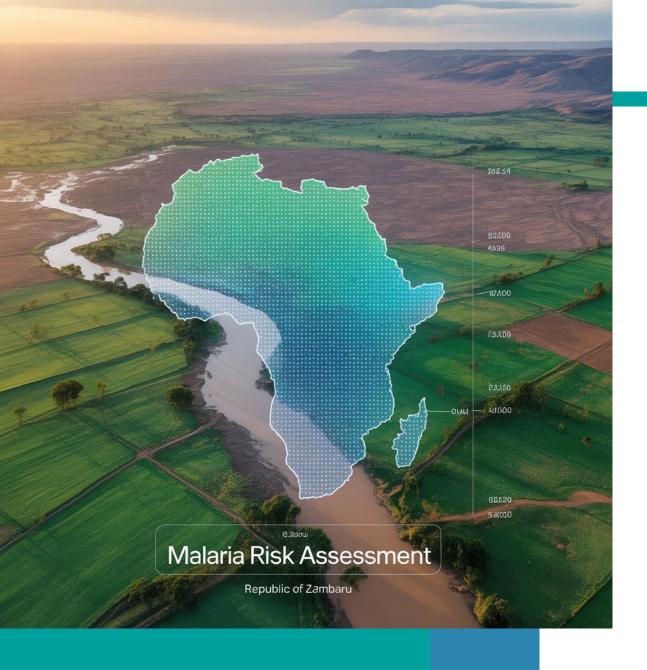
Time-series analysis using LSTM neural networks identifies patterns preceding historical outbreaks.

#### Risk Calculation

Probability scores generated for specific regions with 2-8 week lead time and confidence intervals.

#### Alert Distribution

Automated notifications sent to health officials with recommended response protocols based on risk level.



## Pinpointing Hotspots: Geo-spatial Mapping

From Regional Estimates to Household-Level Precision

- Machine learning algorithms analyze multiple data layers:
  - Satellite imagery of vegetation and standing water
  - Topography and drainage patterns
  - Building density and type
  - Public health infrastructure availability
  - Al: Hyper-localized risk maps identifying specific villages or even households at highest risk, enabling targeted intervention

### **Drug Discovery & Resistance: Racing Against Time**







#### **Faster Drug Discovery**

 Deep learning identifies novel anti-malarial compounds against drug-resistant Plasmodium falciparum 100x faster than traditional methods

#### **Genomic Surveillance**

 ML algorithms analyze parasite genome sequences to detect emerging resistance mutations before they become clinically apparent, enabling proactive adaptation of treatment protocols.

#### **Automated Lab Testing**

 Al-powered robotic systems conduct high-throughput drug assays, analyzing microscopy images in real-time to evaluate compound efficacy against diverse parasite strains.



# Microscopic Vision: Diagnosing Faster

#### **Al-Powered Diagnostics**

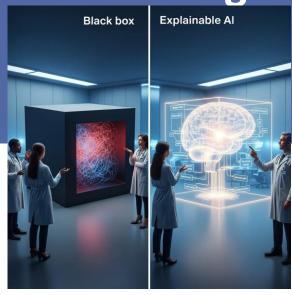
- Machine learning image recognition systems analyze blood smears for malaria parasites with remarkable efficiency:
  - Accuracy: >90%, matching or exceeding human expert microscopists
  - **Speed:** Processing hundreds of slides per hour (vs. dozens per day for humans)
  - Consistency: No fatigue or variation in quality over time
  - Accessibility: Enables expert-level diagnosis in remote areas with limited trained personnel

**Technical Challenges & Limitations** 



#### **Data Quality & Availability**

- Many endemic regions lack reliable historical data. Case reporting is often inconsistent and delayed. Weather station coverage is sparse in rural areas.
- Solution: Satellite-derived proxies and transfer learning from data-rich to data-poor regions.



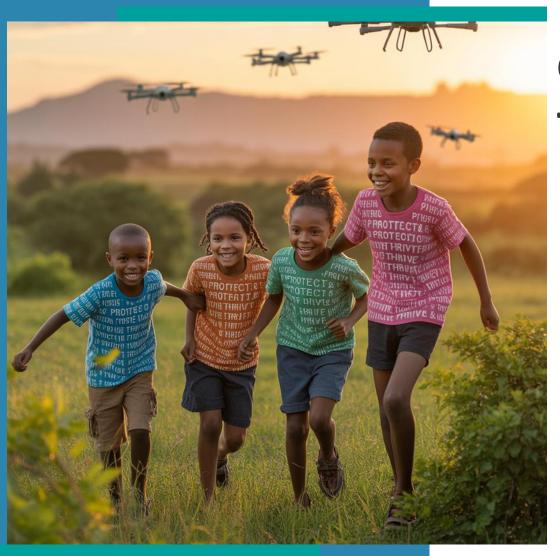
#### **Model Interpretability**

- Complex deep learning models operate as "black boxes," limiting trust from health officials. Critical factors driving predictions remain obscured.
- Solution: Developing explainable
  Al approaches and hybrid models
  that balance accuracy with
  interpretability.



#### **Infrastructure Requirements**

- High-performance computing resources needed for model training. Reliable internet connectivity required for real-time updates. Power supply unstable in many endemic areas.
- Solution: Edge computing solutions and offline-capable applications with periodic synchronization.



# Imagine a Kenya where every child grows up free from the threat of malaria.

- Imagine a nation where outbreaks are predictable, contained, and no longer claim thousands of lives each year.
- Al is not just a tool; it is a catalyst for transformation, a beacon of hope in the fight against an ancient foe.
- Together, we can build this future a malaria-free Kenya where technology empowers communities and saves lives.







## THANK YOU