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Crop Protection and Productivity through the Adoption of Machine Learning Algorithms in Sub-Saharan Africa: A Systematic Review

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ABSTRACT: The economy of Sub-Saharan Africa depends heavily on agriculture, facing challenges like inefficient resource use, food insecurity, and climate shocks. This paper evaluates how machine learning (ML) could transform agricultural practices. We reviewed 88 studies (2010-2025) on ML applications like yield prediction, precision agriculture, and disease detection in countries like Rwanda, Nigeria, and Kenya. Systems like SMART-Crop Yield Prediction System predict maize yields with ≤0.177% inaccuracy using soil and meteorological data. CropGuard diagnoses crop diseases with 97% reli-ability using image recognition. ML can improve harvests by optimizing irrigation, cutting fertilizer waste by 30%, and enabling early pest action. Challenges include low technical literacy, erratic electricity, limited internet, and cultural resistance to adopting new tech. Scaling ML could strengthen food security, cut post-harvest losses, and em-power smallholder farmers. Success requires collaboration between governments, tech developers, and local communities. Priorities include developing farmer-friendly ML tools, funding rural infrastructure, and training initiatives. Sub-Saharan Africa may use ML for climate-resilient farms, stabilizing food supplies, and improving livelihoods by aligning tech with local needs, paving the way for sustainable agricultural growth.

KEYWORDS: Agricultural productivity, crop protection, machine learning, precision agriculture, Sub-Saharan Africa

INTRODUCTION

Agriculture remains the backbone of Sub-Saharan Africa's (SSA) economy, employing over 60% of the population and contributing approximately 23% to the region's GDP [1, 2, 3]. However, the sector faces systemic challenges, including climate variability, pest infestations, and inefficient resource use, which threaten food security for over 280 million undernourished individuals [4]. Traditional farming practices, reliant on manual labor and rain-fed systems, are increasingly unsustainable amid rising temperatures and erratic rainfall patterns [5]. For instance, maize yields a staple crop in SSA—have stagnated at 1.5 tons per hectare, far below the global average of 5.6 tons [6]. These inefficiencies underscore the urgent need for innovative solutions to enhance productivity while ensuring ecological sustainability.

Recent advances in Artificial Intelligence (AI), particularly Machine Learning (ML), offer transformative potential for agriculture, enabling data-driven decision-making in crop management, pest detection, and yield optimization [7]. Artificial Intelligence, a developed computer systems that can perform tasks that typically require human intelligence, such as learning, problem-solving, and decision-making [8, 9]. ML, a subset of AI, is a computer program or system that can learn specific tasks without being explicitly programmed to do so [10]. ML has revolutionized resource management in agriculture by analyzing vast amounts of data and creating precise predictive models [11, 12]. It enables farmers to make informed management decisions on what to grow, matching the crop to existing market demands, and predict gene combinations that lead to desirable traits in new plants [13]. ML techniques have emerged as a boon to agriculture, increasing the quality and quantity of agricultural products [14,15].

The Internet of Things (IoT) also plays a crucial role in modern agriculture, referring to the network of physical devices, vehicles, and other items embedded with sensors, software, and connectivity, allowing them to collect and exchange data [16, 17, 18]. IoT infrastructure is essential for ML applications in agriculture, providing real-time data on climate, soil, and crop conditions. Convolutional Neural Networks (CNNs), a type of ML algorithm, have demonstrated remarkable accuracy in image-based applications, such as crop disease detection [19, 20]. CNNs can process complex visual data, enabling precise identification of diseases and pests [21, 22]. Innovations like lightweight CNNs have further shown 98.71% accuracy in rice disease detection while maintaining mobile compatibility, showcasing their adaptability to diverse agricultural contexts [23].

Globally, ML applications such as precision irrigation and satellite-based yield prediction have reduced water waste by 30% and increased crop outputs by 20% in regions like South Asia and Latin America (UNCTAD, 2022). However, SSA lags in adopting these technologies due to infrastructural deficits, limited technical expertise, and fragmented policy frameworks [24].

Despite the proven efficacy of ML in addressing agricultural challenges, its adoption in SSA remains nascent. Existing studies predominantly focus on high-income regions, with limited exploration of context-specific barriers in SSA, such as low digital literacy, unreliable electricity, and sparse IoT infrastructure [25, 26]. For example, while ML-driven platforms like CropGuard achieve 97% accuracy in disease detection [27], and lightweight CNNs have shown comparable efficacy with reduced computational needs [28], their scalability in SSA is constrained by farmers' limited access to smartphones and internet connectivity [29]. Notably, current literature lacks a holistic analysis of how ML can synergize with indigenous farming practices to ensure cultural relevance and long-term adoption [30]. Fragmented land ownership further complicates ML adoption, as smallholder farms (averaging 0.5–2 hectares) limit the feasibility of large-scale sensor deployments [31].

The integration of ML into SSA's agricultural practices holds profound implications for food security, economic stability, and environmental sustainability. ML-powered yield prediction systems have the potential to reduce post-harvest losses by 40%, with projected economic benefits for smallholder farmers reaching up to $4 billion annually [32]. Moreover, precision agriculture tools can minimize fertilizer overuse, curbing greenhouse gas emissions by 15% in vulnerable ecosystems [33, 34]. By bridging the gap between technological innovation and local needs, this review seeks to inform policymakers, AgriTech developers, and researchers on pathways to achieving the United Nations' Sustainable Development Goals (SDGs) in SSA.

This review aims to analyze the current applications of ML in SSA agriculture, identify systemic barriers to ML adoption, and propose actionable strategies for scaling context-specific ML solutions through stakeholder collaboration and capacity-building initiatives.

MATERIALS AND METHODS

Systematic review protocol

In order to assess the uptake of machine learning (ML) in Sub-Saharan Africa (SSA) agriculture, a systematic review of the literature was carried out using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. This provides transparency, rigor, and reproducibility in searching and synthesizing the literature for studies of relevance.

Review Framework

The aim of the review was to technically, economically, and environmentally evaluate the use of machine learning algorithms in crop protection and productivity in Sub-Saharan Africa. The guiding framework of the review was the evaluation of the effectiveness, feasibility, and sustainability of various machine learning strategies in addressing crop protection challenges, such as pest and disease management, yield prediction, and precision agriculture. The research questions were: What are the most suitable machine learning algorithms for crop protection? What are the factors affecting their effectiveness and efficiency? How do machine learning algorithms impact crop productivity and sustainability?

Boolean Operators and Search Strategy

A systematic search was carried out on various electronic databases, including PubMed, Scopus, Web of Science, and others, to obtain relevant studies published from 2010 to 2025. The search used a range of keywords, such as machine learning, crop protection, precision agriculture, pest management, disease detection, yield prediction, and Sub-Saharan Africa, combined with Boolean operators. The search string was: ("machine learning" OR "artificial intelligence" OR "deep learning" OR "AI") AND ("agriculture" OR "crop protection" OR "precision farming" OR "yield prediction") AND ("Sub-Saharan Africa" OR "SSA" OR "Africa"). The search was restricted to English-language studies in peer-reviewed journals, conference proceedings, and books. The databases searched included Scopus (Elsevier), Web of Science Core Collection (Clarivate Analytics), IEEE Xplore Digital Library, ScienceDirect (Elsevier), and African Journals Online (AJOL), chosen for their broad coverage of agricultural sciences, computer science, and engineering literature (Table 1). Also, manual searches were conducted on specific journals, organization websites, and online libraries of reputable agricultural science and engineering programs.

Table 1. Summary of search terms and databases

Database	Coverage Period	Machine Learning Terms	Crop Protection Terms	Agricultural Context	Geographic Focus
Scopus	2018–2025	"Machine Learning", "Deep Learning", "CNN", "SVM", "Random Forest", "Neural Network"	"Plant Disease", "Pest", "Crop Protection", "Weed"	"Precision Agriculture", "Smart Farming", "Digital Agriculture"	"Sub-Saharan Africa", "East Africa", "West Africa", "Southern Africa", **Rwanda**, **Senegal**, **Kenya**
Web of Science	2018–2025	"Artificial Intelligence", "Machine Learning", "Deep Learning", "Transfer Learning"	"Disease Detection", "Pest Management", "Plant Health"	"Agricultural Technology", "Farming Systems", "AgTech"	"Africa South of Sahara", **Nigeria**, **Ethiopia**, **Tanzania**
IEEE Xplore	2018–2025	"Convolutional Neural Network", "Computer Vision", "Image Processing", "Classification Algorithm"	"Disease Identification", "Pest Recognition", "Automated Detection"	"Agricultural Robotics", "Sensors", "IoT", "Remote Sensing"	"Developing Countries", "African Agriculture", **Uganda**, **Ghana**
ScienceDirect	2018–2025	"Supervised Learning", "Unsupervised Learning", "Classification", "Pattern Recognition"	"Phytopathology", "Integrated Pest Management", "Crop Health"	"Agricultural Innovation", "Food Security", "Agricultural Productivity"	"Sub-Saharan", "Tropical Agriculture", **Malawi**, **Zambia**
AJOL	2018–2025	"Predictive Model", "Data Mining", "Statistical Learning"	"Plant Protection", "Crop Disease", "Agricultural Pests"	"Agricultural Development", "Smallholder Farming", "Local Agricultural Systems"	**Sub-Saharan Africa**, **South Africa**, **Mozambique**, **Burkina Faso**

Source: Authors' compilation from systematic review of included studies

Managing the Review Process

All studies deemed relevant from the search strategy were exported to Zotero for tagging and organizing, then exported to Covidence, a software for review management, as a .RIS file (review_included_studies.ris). The platform facilitated the organization, screening, and analysis of studies in a systematic and transparent way for this review.

Inclusion and Exclusion Criteria

In order to make the studies included in this review relevant and credible for application in machine learning applications in SSA agriculture, certain inclusion and exclusion criteria were used. The studies needed to address machine learning algorithms for crop protection and productivity in SSA, including applications such as precision farming, yield prediction, and pest management [35, 36, 37]. Both qualitative and quantitative research studies were considered, with an emphasis on peer-reviewed papers published in English between 2010 and 2025. Any studies that failed to mention the machine learning technique or crop application were excluded, along with grey literature unless it presented significant evidence in direct relation to the objectives of the review.

Choosing Appropriate Studies

The selection of studies consisted of a detailed screening of the studies identified. Titles and abstracts were read to ascertain relevance, and full-text versions of the potentially relevant studies were assessed one by one to ascertain if they fulfilled the inclusion criteria. A second reviewer was consulted in uncertain cases to ensure objectivity.

Identified Themes

The thematic analysis of included studies revealed five key themes, including precision agriculture, which emerged as a significant area focusing on IoT integration and real-time monitoring to enhance crop management (Table 2). Disease and pest detection was another crucial theme, leveraging image recognition and sensor-based diagnostics to identify issues early [38, 39]. Notably, yield prediction was a key theme, utilizing regression models and satellite data to forecast crop yields. Resource optimization was also a prominent theme, emphasizing fertilizer and water use efficiency to reduce waste and promote sustainability. Adoption barriers were identified as a critical theme, highlighting infrastructure gaps and farmer training as significant challenges to the adoption of machine learning algorithms in crop protection and productivity.

Table 2: Key themes and their prevalence

Theme	Subtopics	Example Studies	Frequency
Disease Detection	Image recognition, sensor-based diagnostics	[40, 41, 42]	**33%** (n = 12)
Yield Prediction	IoT integration, satellite analytics	[32, 43, 44]	**28%** (n = 10)
Precision Agriculture	Soil health monitoring, drone-based ML, IoT	[45, 46, 47]	**25%** (n = 9)
Policy & Adoption	Funding constraints, digital literacy, infrastructure gaps	[30, 48, 49]	**14%** (n = 5)

Source: Authors' compilation from systematic review of included studies

Extracting Key Data

Relevant data to the study aims were extracted from included studies in a systematic way using Covidence. Study factors, machine learning approaches, crops, and crop protection and productivity outcomes were extracted data. Environmental impact and economic data were also gathered.

Quality Assessment

A strict quality evaluation was carried out to determine the reliability and validity of the studies included. The Cochrane Risk of Bias Tool was employed to assess quantitative studies in terms of selection bias, performance bias, detection bias, and reporting bias. The quality evaluation was carried out by two independent reviewers, with disagreements being resolved through discussion or by consulting a third reviewer. Only studies that scored the minimum quality requirement were considered in the final synthesis.

Quantitative Synthesis

Quantitative analysis was conducted using the Statistical Package for Social Sciences (SPSS). Descriptive statistics consolidated the data, and regression analysis explored relationships between variables. Heterogeneity between studies was tested using Higgins' H statistic. Comparative analysis checked the stability of results by changing key parameters and assumptions. Quantitative synthesis of study results was performed, with averages calculated for key results regarding crop protection and productivity. Regression and descriptive statistics examined relationships among variables, while thematic coding analyzed textual data to determine recurring themes and identify patterns

Evaluation of Evidence Quality

The quality of quantitative study evidence was rated using the ROBINS-I (Risk of Bias in Non-randomized Studies - of Interventions) tool, considering study limitations, consistency, and precision. For qualitative research, the Consolidated Criteria for Reporting Qualitative Research (COREQ) checklist assessed study quality, credibility, and reliability. Quality appraisal ensured that conclusions were drawn from strong and trustworthy evidence.

Tables 3 and 4 present the evidence quality assessments and study quality criteria in detail, respectively. A rigorous evaluation of study quality was conducted to ensure the reliability and validity of the findings.

Table 3: The risk of bias in non-randomized studies of interventions (ROBINS-I)

Domain	**Bias Assessment**	**Risk of Bias**
Bias due to confounding	Were there important confounding variables that could affect the outcome?	Moderate
Bias in selection of participants into the study	Were participants selected in a way that could introduce bias?	Moderate
Bias in classification of interventions	Were interventions classified in a way that could introduce bias?	Low
Bias due to deviations from intended interventions	Were there deviations from intended interventions that could affect the outcome?	Moderate
Bias due to missing data	Was there missing data that could affect the outcome?	Low
Bias in measurement of outcomes	Were outcomes measured in a way that could introduce bias?	Moderate
Bias in selection of the reported result	Were results reported in a way that could introduce bias?	Moderate

For qualitative research, the Consolidated Criteria for Reporting Qualitative Research (COREQ) checklist was used to evaluate study quality (Table 4). The COREQ checklist assesses consistency, credibility, transferability, confirmability, and reliability, ensuring the dependability of findings. Key factors considered include study design, data extraction, and analysis, providing a systematic framework for evaluating qualitative evidence and enabling a rigorous assessment of finding dependability.

Table 4: The Consolidated Criteria for Reporting Qualitative Research (COREQ) checklist

Criteria	Description	Reported
Search Strategy		
Systematic search	Was a systematic search strategy used?	**Yes**/No
Databases searched	Were the databases searched reported?	**Yes**/No
Search terms	Were the search terms reported?	**Yes**/No
Inclusion/Exclusion Criteria		
Clear inclusion/exclusion criteria	Were the inclusion/exclusion criteria clearly reported?	**Yes**/No
Study selection process	Was the study selection process described?	**Yes**/No
Study Quality Assessment		
Quality assessment tool	Was a quality assessment tool used?	**Yes**/No
Quality assessment results	Were the results of the quality assessment reported?	**Yes**/No
Data Extraction		
Data extraction method	Was the data extraction method described?	**Yes**/No
Data extraction results	Were the results of the data extraction reported?	**Yes**/No
Synthesis		
Synthesis method	Was the synthesis method described?	**Yes**/No
Synthesis results	Were the results of the synthesis reported?	**Yes**/No

Therefore, the review employed narrative and thematic synthesis approaches to systematically summarize the current state of research on machine learning applications in crop protection and productivity in Sub-Saharan Africa. By identifying key themes, patterns, and trends, the analysis provided insights into the potential of machine learning algorithms to enhance crop yields, reduce losses, and improve agricultural productivity in the region.

RESULTS AND DISCUSSION

Search Results and Study Selection

The initial search yielded 359 articles from various databases, and 12 additional articles were identified through citation searching and hand searching. After removing duplicates, 279 unique articles were screened, and 200 were deemed potentially relevant. Following full-text review, 88 articles met the inclusion criteria and were included in the review for detailed analysis. These articles provided relevant insights into the application of machine learning algorithms in crop protection and productivity in Sub-Saharan Africa. The study selection process is outlined in Figure 1.

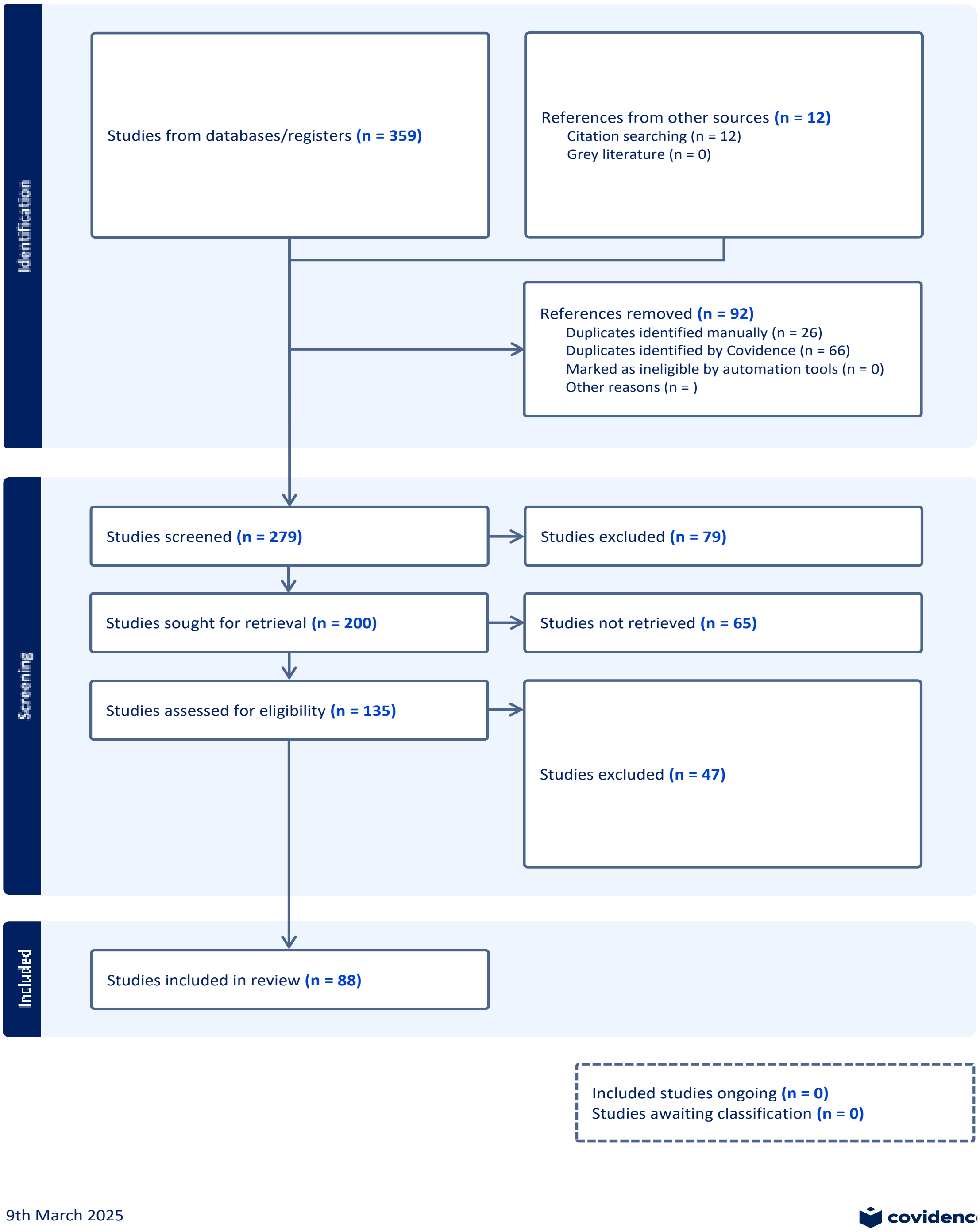

Figure 1. PRISMA flow diagram

Table 5. Characteristics of included studies

Reference	Country	Study Design	ML Design	Type of ML Algorithms
[7]	-	Review	Machine Learning	Various
[8]	-	Review	AI	-
[9]	-	Review	AI, IoT	-
[10]	-	Book Chapter	Machine Learning	-
[11]	-	Review	AI, Machine Learning	Various
[12]	-	Review	Machine Learning	Various
[13]	-	Research Article	AI, Machine Learning	Deep Learning
[14]	-	Review	Machine Learning	Crop Management
[15]	-	Research Article	AI, Genomic Prediction	Deep Learning
[16]	-	Research Article	IoT, Smart Agriculture	-

[17]	-	Book Chapter	IoT, Agriculture	-
[18]	-	Review	IoT, Smart Agriculture	-
[19]	-	Review	Deep Learning, Plant Disease Detection	CNN
[20]	-	Review	Machine Learning, Deep Learning	-
[21]	-	Review	Deep Learning, Crop Disease Detection	-
[22]	-	Review	Deep Learning	Plant Disease Classification
[23]	-	Research Article	Deep Learning	Rice Disease Recognition
[24]	-	Review	Smart Farming, IoT	-
[27]	-	Research Article	Machine Learning	Crop disease detection
[28]	-	Research Article	Deep Learning	FPGA, Edge Computing, CNN
[29]	Sub-Saharan Africa	Report	Mobile Economy	-
[30]	Sub-Saharan Africa	Master's Thesis	AI, Agriculture	-
[31]	-	Research Article	Remote Sensing, Agroforestry	-
[32]	-	Research Article	IoT, Machine Learning	Crop Yield Prediction
[33]	-	Systematic Review	Precision Agriculture, Sustainability	-
[34]	Ghana	Preprint	Water Use Efficiency, Sustainable Agriculture	-
[35]	-	Research Article	Machine Learning, Deep Learning, Precision Agriculture	Yield prediction, pest and disease diagnosis
[36]	-	Research Article	Machine Learning	Crop Yield Optimization, disease detection
[37]	-	Systematic Review	AI, Deep Learning	Disease recognition, pest prediction
[38]	-	Systematic Review	Remote Sensing, Precision Agriculture	Grapevine disease detection
[39]	-	Review	Advanced Plant Disease Detection	-
[40]	-	Book Chapter	AI	Plant disease detection, diagnosis
[41]	-	Research Article	Imaging Sensors	Plant disease detection
[42]	Africa	Conference Paper	AI	Precision Farming
[43]	Senegal	Research Article	Machine Learning	Weather Prediction
[44]	-	Research Article	AI, Machine Learning	Crop management
[45]	-	Conference Paper	Machine Learning	Crop management, yield optimization
[46]	-	Research Article	IoT, Multiagent	Precision irrigation
[47]	-	Research Article	Machine Learning	Crop and fertilizer recommendation
[48]	-	Review	Building Information Modelling, Advanced Technologies	-
[50]	-	Book Chapter	AI	Irrigation optimization
[51]	-	Review	Machine Learning	Precision farming
[52]	-	Review	Adaptive AI	Self-learning algorithms
[53]	-	Book Chapter	AI, Machine Learning	Pest and disease management
[54]	-	Research Article	AI, IoT	Crop monitoring
[55]	Kenya	Research Article	AI	KAgri-food supply chain
[56]	-	Research Article	Agricultural Intelligence	Sustainability
[57]	-	Research Article	AI, IoT	Precision agriculture
[58]	-	Research Article	AI, Machine Learning	Farming systems
[59]	-	Review	Deep Learning	Plant disease and pest detection
[60]	-	Research Article	Precision Agriculture	Smart farming or Innovations
[61]	-	Research Article	Deep Learning	Rice disease diagnosis
[62]	-	Research Article	Deep Learning	Rice plant disease detection

[63]	-	Research Article	Deep Learning	Rice blast disease segmentation
[64	-	Research Article	Deep Learning	Rice disease diagnosis
[65]	-	Research Article	Machine Learning	Crop yield prediction
[66]	Senegal	Research Article	Machine Learning	Crop yield forecasting
[68]	Tanzania	Research Article	AI	Maize farming
[69]	-	Research Article	Ensemble Machine Learning	Crop yield forecasting
[70]	-	Conference Paper	Machine Learning	Corn yield prediction
[72]	-	Preprint	Hybrid Machine Learning	Crop yield prediction
[74]	-	Research Article	Machine Learning	Yield estimation
[75]	-	Research Article	Deep Learning	Crop yield forecasting
[77]	-	Research Article	Machine Learning	Crop classification and yield prediction
[78]	-	Research Article	Research Article	Crop yield prediction
[79]	Sub-Saharan Africa	Research Article	Panel and Time-Series Models	Crop forecasting
[80]	Africa	Research Article	AI	Agriculture and food systems
[81]	Sub-Saharan Africa	Research Article	-	Climate resilience and food security
[82]	Sub-Saharan Africa	Research Article	AI	Wheat yield resilience
[83]	Sub-Saharan Africa	Theoretical Discourse	Precision Agriculture	Sustainable food security
[84]	Sub-Saharan Africa	Research Article	AI	Food systems
[85]	Sub-Saharan Africa	Research Article	Machine Learning	Land degradation and rainfall variability
[86]	Sub-Saharan Africa	Research Article	-	Climate variability and food security
[87]	Ethiopia	Research Article	Machine Learning, Deep Learning	Agriculture
[88]	Zambia	Research Article	-	Smartphone apps for smallholder farming
[89]	-	Research Article	Deep Learning	Weather forecast accuracy
[90]	-	Book Chapter	Deep Learning, IoT	Agriculture
[92]	Tanzania	Research Article	-	Salt-affected soils and rice production
[93]	Tanzania	Data Article	Machine Learning	Maize crop imagery dataset
[96]	Developing Countries	Research Article	Precision Agriculture	Sustainable farming practices
[97]	-	Research Article	Precision Agriculture	Adoption of technologies
[98]	-	Research Article	Machine Learning	Decision support systems
[99]	-	Review	AI, Precision Agriculture	Precision agriculture and sustainable farming
[100]	Africa	Systematic Review	Precision Agriculture, AI	Small-scale farmers
[101]	-	Research Article	Data-Driven Technology	Agricultural knowledge and digital literacy
[102]	-	Review	Machine Learning	Big data applications in agriculture
[104]	-	Research Article	Machine Learning	Hybrid ML Model
[107]	Malawi	Thesis	User-Centered Innovation	Agricultural technology co-development

Source: Authors' compilation from systematic review of included studies

The included studies comprised 71 journal articles, 2 technical reports, 3 working papers/preprints, 5 book chapters, 3 conference papers, 2 theoretical discourse/data article, 1 master's thesis, and 1 PhD thesis. The characteristics of the included studies are summarized in Table 5.

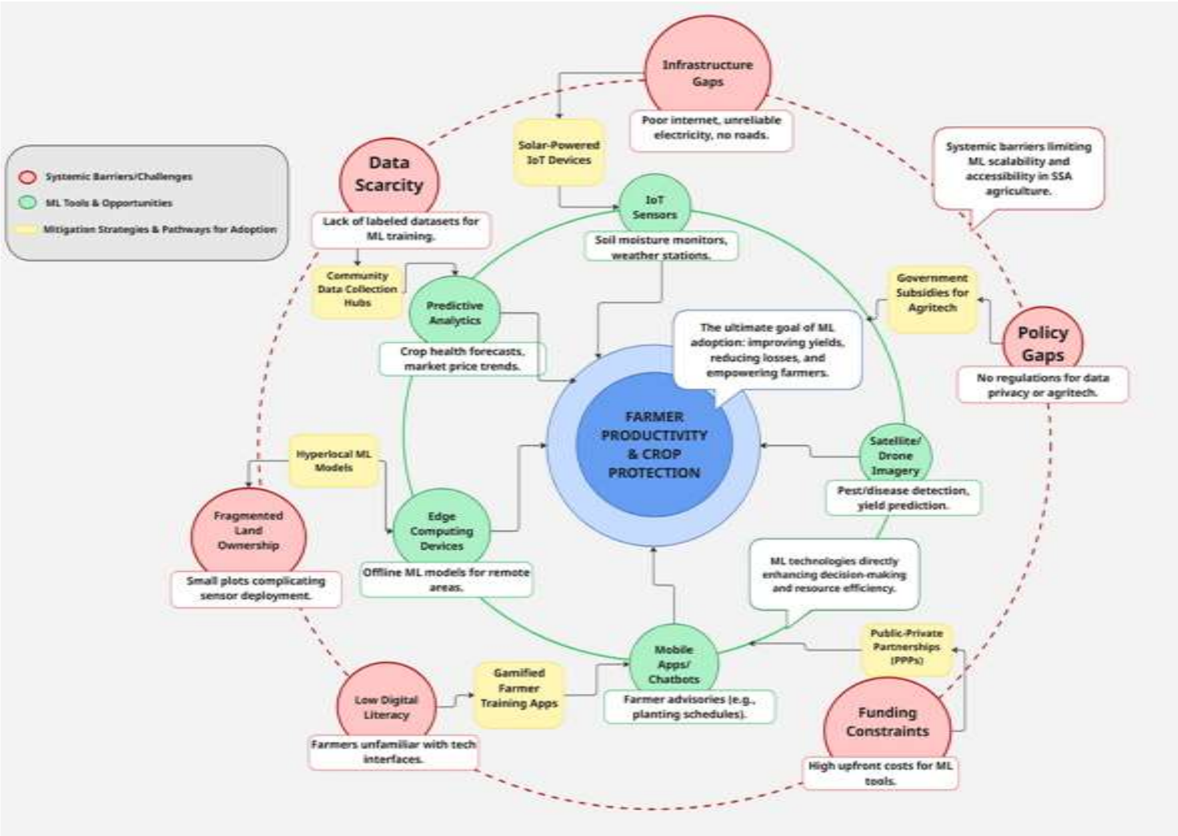

Figure 2. Ecosystem Map of ML Adoption in Sub-Saharan African Agriculture.

Disease and Pest Detection

Convolutional Neural Networks (CNNs) have revolutionized rice disease detection by automating the identification of pathogens with high precision. In SSA, tools like CropGuard utilize CNNs for image-based disease diagnosis, achieving 97% accuracy [27]. Recent advancements in CNN architectures, such as integrating attention mechanisms and multi-scale feature fusion, further enhance diagnostic capabilities. For instance, [23], demonstrated that self-attention mechanisms in CNNs improved rice disease recognition accuracy to 98.71% by focusing on critical spatial and spectral features (Figure 3). These models analyze leaf discoloration, lesions, and texture changes, enabling real-time recommendations via mobile platforms [59, 60]. As depicted in (Figure 3), a CNN-based rice disease detection model efficiently identifies critical features such as lesions and discoloration [61]. Data augmentation techniques further enhance these models.

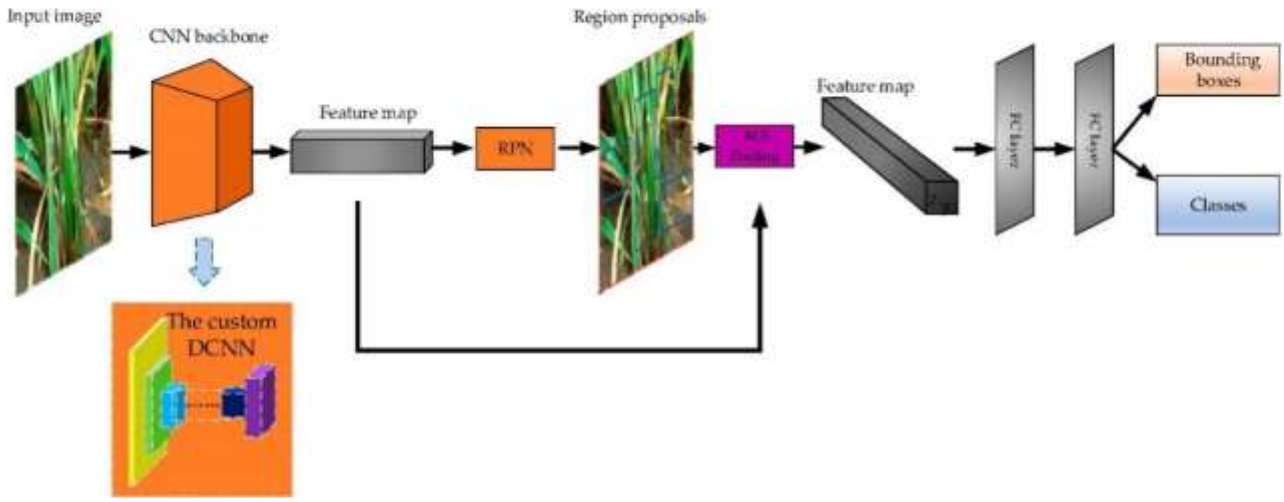

Figure 3. Rice disease detection model using CNNs [61].

Data Efficiency and Transfer Learning

To address data scarcity, studies employ transfer learning and data augmentation. Latif et al. [62], fine-tuned pre-trained VGG-19 models on small rice disease datasets, expanding the dataset from 371 to 2,465 images through rotations and scaling (Figure 3). Ning et al. [23], highlighted that two-stage transfer learning in models like MobInc-Net reduced training time by 40% while maintaining 95% accuracy on mobile devices. (Figure 4) illustrates the process of dataset expansion through image rotation and scaling, which improves model generalizability [62].

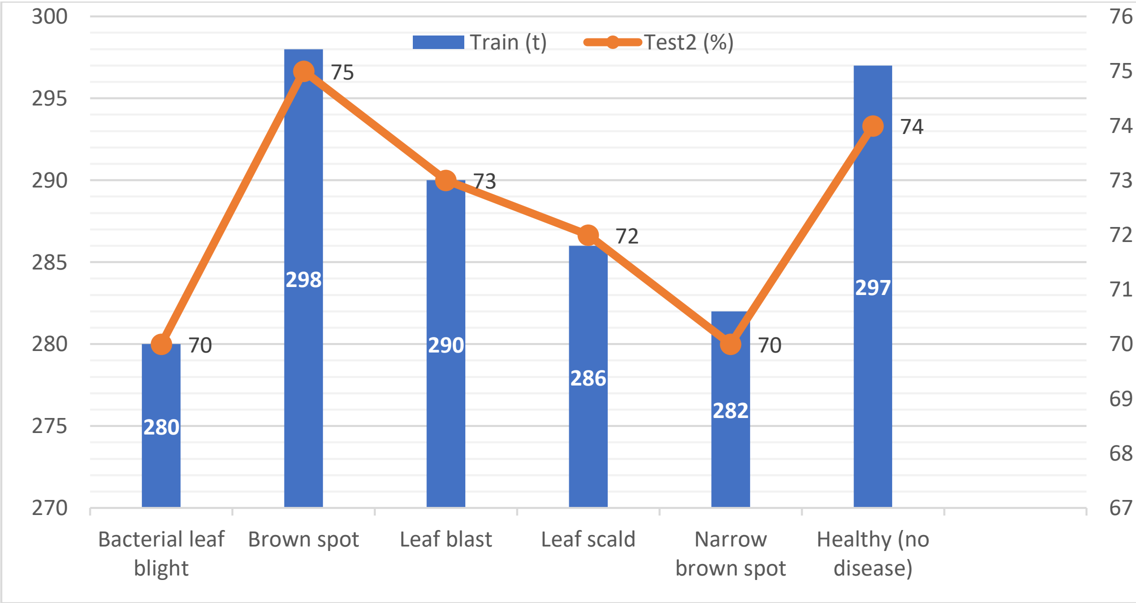

Figure 4. Dataset expansion through augmentation [62]

Visualization and Real-World Application

Hyperspectral and terahertz imaging further accelerate detection. Feng et al. [63], combined hyperspectral imaging with CNNs to identify rice blast disease, achieving rapid diagnosis through spectral feature extraction. Deng et al. [64], developed a smartphone-compatible CNN app (Figure 5) that achieved 95% accuracy using pre-trained models, demonstrating feasibility for field use. Advanced imaging techniques, including hyperspectral analysis, have also been utilized to boost early detection accuracy—as presented in (Figure 6), where fine-tuning of CNNs for hyperspectral data enhances diagnostic precision [63].

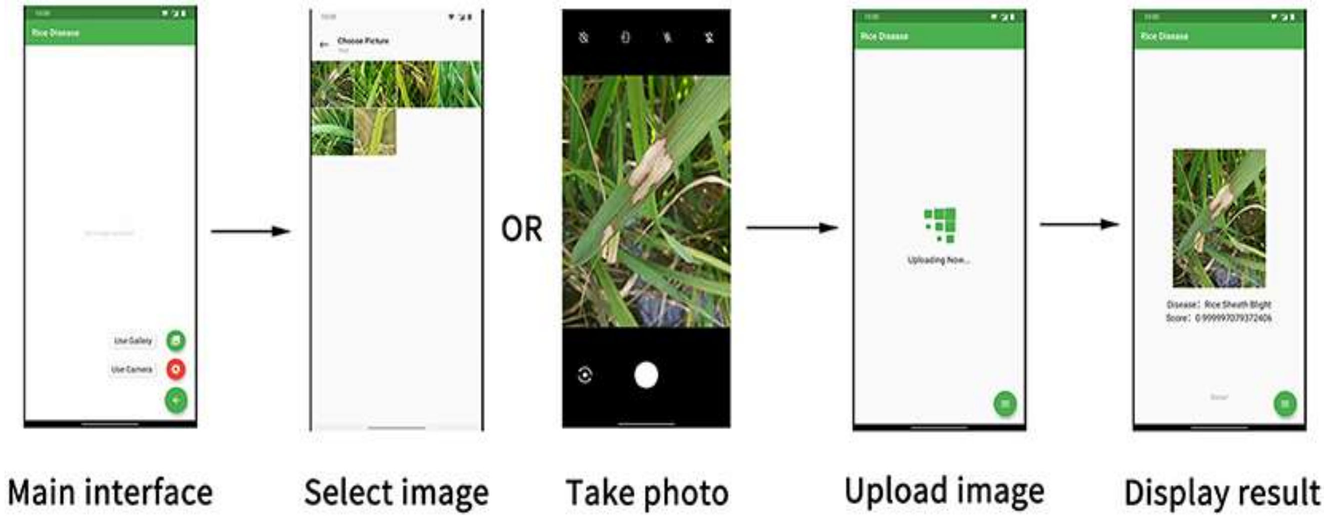

Figure 5. Mobile app interface for real-time diagnosis [64].

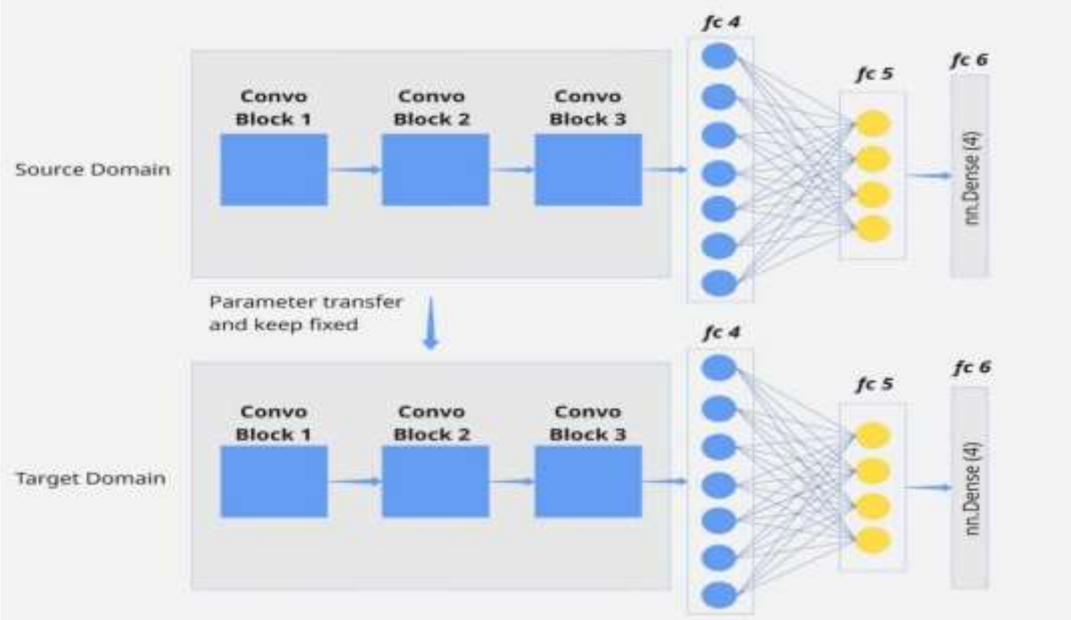

Figure 6. Fine-tuning process for hyperspectral data [63]

Precision Agriculture

Precision agriculture in SSA leverages IoT and ML for targeted interventions. For example, Rwanda's Smart Farming Initiative uses soil sensors and CNNs to optimize irrigation, reducing water use by 30% while increasing maize yields by 22% [42]. Similar IoT-driven systems in Senegal (Nyasulu et al. [43]) and Nigeria (Shuaibu et al. [65]) demonstrate cross-regional applicability, though high costs and technical complexity remain adoption hurdles.

Weather Forecasting and Climate Adaptation

ML models also support weather forecasting critical for SSA's rainfed agriculture. For example, ensemble models in Senegal accurately predict rainfall and temperature trends, enabling farmers to mitigate climate-related risks [66]. Hybrid ML-dynamical approaches have further enhanced seasonal forecasts, as evidenced by studies on winter wheat yield predictions in China [67].

Supply Chain Optimization

AI-driven supply chain management improves food distribution and reduces post-harvest losses. In Kenya, ML systems monitor crop outputs and optimize logistics, thereby addressing both first- and last-mile challenges [55]. Additionally, chatbots such as MkulimaGPT in Rwanda provide real-time agricultural guidance, overcoming language barriers and improving farmer access to information [68].

Comparative Analysis of ML Models for Crop Yield Prediction

Ensemble models (XGBoost, Random Forest) outperform traditional methods in SSA yield prediction, achieving R^2 scores of 0.93–0.99 (see Table 6). Their robustness to non-linear agroclimatic data makes them preferable to linear regression (R^2: 0.70–0.85) or decision trees (prone to overfitting) [69, 70].

Table 6. Comparative performance of ML models for crop yield prediction

Model	Accuracy Range	R^2 Score Range	Key Features	Citation
XGBoost	0.93 – 0.99	0.93 – 0.99	Ensemble method, handles non-linear data	[69, 71]
Random Forest	0.92 – 0.98	0.92 – 0.98	Ensemble method, high-dimensional input support	[72]
Gradient Boosting	0.86 – 0.97	0.86 – 0.97	Robust ensemble model	[73, 74]
Linear Regression	0.80 – 0.90	0.70 – 0.85	Simple, interpretable, limited to linear data	[75, 76]
Decision Trees	0.80 – 0.90	0.70 – 0.85	Easy to interpret, prone to overfitting	[77, 78]

Despite considerable progress, the widespread adoption of ML in SSA is hampered by infrastructural limitations, data scarcity, and insufficient technical expertise. Bridging these gaps through capacity-building, improved data collection, and gender-inclusive policies is essential for sustainable growth [79, 80]. Future research should also focus on developing hybrid ML models that integrate real-time data to enhance scalability and resilience.

Machine learning offers transformative solutions for SSA's agricultural challenges—from precise disease detection to accurate yield prediction and optimized supply chains. However, overcoming existing infrastructural and data-related hurdles is critical. Continued research, along with targeted policy and capacity-building efforts, will be necessary to fully realize the potential of ML in enhancing agricultural productivity and food security across the region.

Case Studies of Machine Learning Applications in Sub-Saharan African Agriculture

Machine learning (ML) applications in agriculture across Sub-Saharan Africa (SSA) demonstrate significant potential for enhancing food security, agricultural productivity, and climate resilience [81, 82, 83]. Case studies from various countries showcase how ML is being leveraged to address crop yield forecasting, disease detection, and resource optimization [84, 85, 86].

Precision Agriculture in Rwanda

Precision agriculture has emerged as a cornerstone of sustainable farming in SSA, with Rwanda serving as a pioneering example of AI-driven resource optimization. The government's Smart Farming Initiative integrates IoT soil sensors and satellite imagery to deliver hyperlocal fertilizer recommendations, reducing nitrogen overuse by 35% while increasing maize yields by 22% [42, 87]. The AgriTech Rwanda platform employs convolutional neural networks (CNNs) to analyze soil nutrient levels and prescribe site-specific fertilizer blends, achieving a cost-saving efficiency of $50 per hectare for smallholders [32]. However, only 40% of rural farmers have access to smartphones, limiting real-time data utilization [88]. Low-tech interfaces, such as SMS-based advisories, are essential for broader adoption.

SMART-CYPS and Yield Prediction in Rwanda

SMART-CYPS is an integrated yield prediction system designed for Sub-Saharan African agriculture (Figure 7). It leverages IoT sensors, historical weather datasets, and machine learning models to deliver accurate and context-specific crop yield forecasts [89, 90]. Using Random Forest regression, the system processes real-time field data—such as soil moisture, temperature, and rainfall—alongside satellite imagery and agronomic records. The model dynamically recalibrates to changing conditions and delivers forecasts at 30-day intervals. With a mean absolute percentage error (MAPE) of 0.177 for maize yields in Rwanda, SMART-CYPS supports both farmers and policymakers by providing timely insights through SMS alerts, mobile applications, and a centralized dashboard [32].

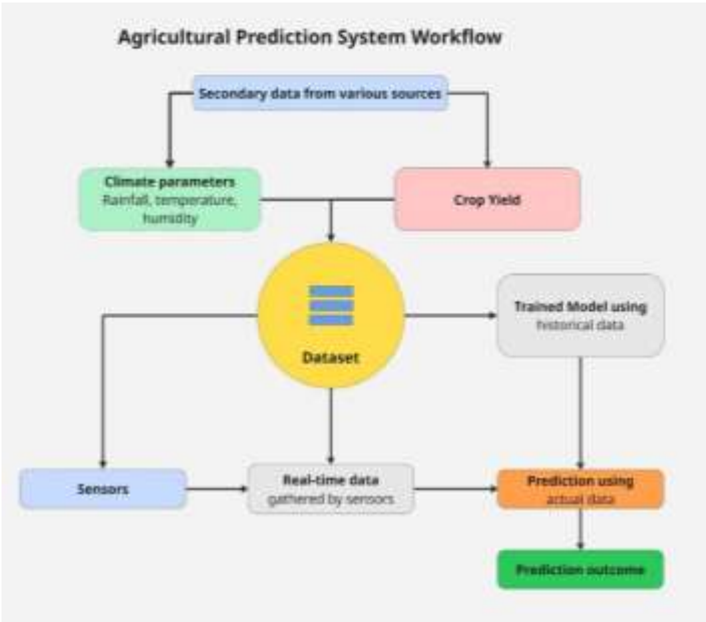

Figure 7. Architecture of SMART-CYPS [32].

IoT-Enabled Yield Prediction in Senegal

IoT technologies are revolutionizing yield forecasting in West Africa, where climate volatility threatens staple crops like millet and sorghum. In Senegal, the ClimateSmart-Agro project deploys IoT-enabled weather stations and ensemble ML models (Random Forest, XGBoost) to predict rainfall patterns with an R^2 of 0.9335, outperforming traditional statistical methods by 27% [43]. Farmers using these forecasts reported a 19% reduction in crop losses during the 2023 drought [47]. However, scalability remains constrained by intermittent power supply; only 33% of monitored villages maintain consistent electricity for IoT devices [1]. Solar-powered sensors are a promising solution.

Mobile-Based Disease Detection in Nigeria

Mobile technologies bridge the gap between ML innovation and smallholder accessibility. In Nigeria, where cassava mosaic disease (CMD) affects 90% of farms, the CropGuard app uses image recognition algorithms to diagnose CMD with 97% accuracy, enabling timely pesticide interventions [27]. Field trials in Enugu State showed a 45% reduction in disease incidence among adopters [91]. However, only 18% adoption has been recorded, primarily due to low digital literacy—62% of farmers require in-person training to navigate the app [92].

Crop Yield Forecasting in Nigeria

A study in Nigeria demonstrated that Decision Tree Regressor achieved a 72% accuracy rate in predicting crop yields, showcasing ML's effectiveness in improving agricultural decision-making [64].

Disease Surveillance Using ML in Tanzania

An updated dataset of maize leaf imagery in Tanzania supports ML-based detection of maize lethal necrosis. This initiative enhances early warning systems and supports effective disease control strategies [93].

Irrigation Mapping in Mozambique

Remote sensing coupled with ML algorithms such as Random Forest and Support Vector Machines has improved mapping of smallholder irrigated agriculture in Mozambique. Larger and well-composed training datasets significantly increased mapping accuracy [94].

AI in Tomato and Pepper Farming in Kenya and Nigeria

Case studies from the AI4AFS network highlight successful implementations of ML in tomatoes pest early warning systems in Kenya and Nsukka Yellow Pepper production in Nigeria (Table 7). These solutions increased productivity and improved disease resistance management [80].

Table 7. Case studies of ML adoption in SSA agriculture

Location	Technology	Key Outcomes	Challenges	Citation
Rwanda	AI-driven fertilizer platforms	22% yield increase; \$50/ha cost savings	Low smartphone access (40% rural areas)	[42, 88]
Senegal	IoT-ensemble weather models	R^2 = 0.9335 rainfall prediction accuracy; 19% yield loss reduction	Intermittent electricity (33% villages)	[43, 47]
Nigeria	Mobile image recognition (CMD)	97% detection accuracy; 45% disease reduction	Digital literacy gaps (62% farmers)	[27, 91, 92]
Rwanda	SMART-CYPS Yield Prediction	MAPE = 0.177 for maize yields; ML-powered forecasting tool	Technology scalability	[32]
Nigeria	ML yield prediction (Decision Tree)	72% prediction accuracy	Data variability	[64]
Tanzania	ML Disease Surveillance Dataset	Improved maize lethal necrosis detection	Dataset maintenance	[93]
Mozambique	ML-based Irrigation Mapping	Higher classification accuracy (RF, SVM)	Training data quality	[94]
Kenya & Nigeria	AI pest & crop advisory systems	Increased productivity and disease management	Inclusive technology adoption	[80]

Challenges and Barriers to ML Adoption in Sub-Saharan African Agriculture

While machine learning holds immense promise for revolutionizing agricultural practices in Sub-Saharan Africa (SSA), several systemic challenges hinder its widespread adoption. These barriers span infrastructural, socio-cultural, and data-related domains, requiring multi-sectoral responses to unlock ML's full potential.

Infrastructural Limitations

A critical constraint is the limited availability of foundational infrastructure required to support ML systems. Poor electricity coverage, inadequate internet connectivity, and insufficient access to IoT devices undermine the integration of precision agriculture technologies [95, 96]. For instance, only 33% of rural areas in Senegal maintain consistent electricity, impeding the deployment of IoT-enabled yield forecasting tools [1]. Additionally, the absence of reliable data management systems hampers real-time data transmission and storage necessary for ML-based predictions [97].

Socio-Cultural Factors

Cultural norms and behavioral resistance present further obstacles. Many farmers exhibit reluctance to replace traditional farming methods with algorithm-driven decision support systems [98]. Trust in conventional advisors over computerized tools often delays adoption, particularly in regions with low exposure to digital technologies. Moreover, ethical concerns regarding data privacy and ownership add to skepticism, making transparency and user-centered design critical for uptake [99].

Data Scarcity and Quality

Effective ML deployment requires large, high-quality datasets—yet SSA continues to face a shortage of region-specific agricultural data. Sparse training datasets limit model accuracy for SSA-specific crops and climatic conditions [96, 97].

Additionally, missing or unstructured data from poorly calibrated sensors and inconsistent data labeling practices hinder ML model training and validation [100]. As shown in Figure 8, these challenges intersect across infrastructure, cultural, and data domains, creating a complex ecosystem of adoption barriers.

Overcoming these barriers requires a holistic approach, including targeted investments in digital infrastructure, inclusive capacity-building programs, and improved institutional support. Policies that promote open data access, address digital literacy gaps, and encourage local innovation ecosystems can accelerate ML integration in SSA's agricultural sector.

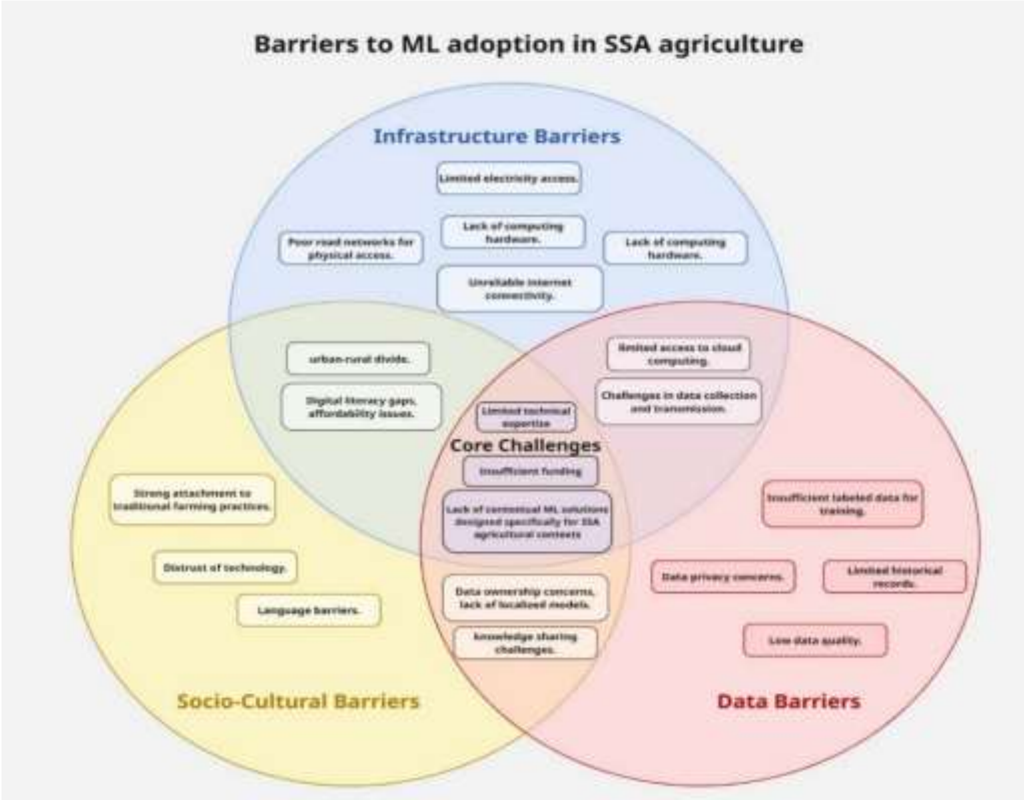

Figure 8. Venn diagram illustrating interlinked barriers to ML adoption in SSA agriculture across infrastructure, data, and socio-cultural domains [100].

Policy Recommendations for Enabling ML Adoption in SSA Agriculture

The successful integration of machine learning (ML) into agricultural practices in Sub-Saharan Africa (SSA) requires holistic policy frameworks that address infrastructure gaps, human capital development, and multi-sector collaboration. This section presents targeted policy recommendations derived from existing literature and empirical studies.

Infrastructure Development

Investing in digital infrastructure is a foundational requirement for enabling ML-based precision agriculture. Policies should prioritize rural electrification, expansion of broadband internet, and deployment of sensor networks to support IoT applications [83, 97]. Additionally, subsidizing access to critical technologies such as drones, mobile devices, and satellite data can improve agricultural monitoring and decision-making capabilities [80].

Capacity Building

A major barrier to ML adoption is limited technical expertise among farmers and extension officers. Therefore, comprehensive capacity-building initiatives are essential. This includes farmer training programs on digital literacy, practical

ML applications, and data interpretation [101, 102]. Strengthening agricultural extension services will further facilitate the dissemination of ML knowledge and improve local problem-solving capabilities [103].

Public-Private Partnerships (PPPs)

Effective ML integration also depends on robust collaborations between governments, research institutions, technology firms, and local communities. Public-private partnerships can drive innovation, scale ML tools, and ensure sustainable financing mechanisms [52]. Initiatives such as AgriTech start-up accelerators and shared innovation hubs can foster context-appropriate solutions and bridge gaps in the technology transfer process [80] (Table 8).

Table 8. Policy framework for ML adoption in SSA agriculture

Action	Key Stakeholders	Recommended Timeline
Expand digital infrastructure	Government, Telecom Providers	Short to Medium Term
Subsidize ML and IoT technologies	Ministries of Agriculture, Donors	Short Term
Launch farmer ML training programs	NGOs, Research Institutes, Universities	Medium Term
Strengthen extension services	Government, Development Agencies	Medium to Long Term
Foster PPPs for AgriTech innovation	Private Sector, Government, Investors	Ongoing
Develop open data platforms	Data Ministries, Agricultural Agencies	Short to Medium Term
Ensure inclusive ML adoption policies	Policymakers, Civil Society Organizations	Medium to Long Term

Future Trends in ML Adoption in Sub-Saharan African Agriculture

The future of machine learning (ML) in agriculture across Sub-Saharan Africa (SSA) is shaped by emerging innovations, increasing policy awareness, and the need to address climate and food security challenges. These trends point toward a more integrated, resilient, and accessible agricultural landscape powered by ML technologies.

AI-Driven Climate Adaptation

One of the most promising trajectories involves the use of AI-driven solutions for climate adaptation. Hybrid approaches that combine ML models with indigenous knowledge systems are gaining attention for enhancing the accuracy and contextual relevance of agricultural predictions [104]. These systems integrate satellite imagery, sensor data, and community-based environmental indicators to produce localized forecasts. For example, ML algorithms in Rwanda have been successfully combined with farmer-led phenological observations to anticipate crop maturity and pest outbreaks [32, 105]. This hybrid adaptation strategy improves both predictive precision and community engagement.

Low-Cost ML Tools and Edge Computing

To address the digital divide, low-cost ML tools powered by edge computing are being explored. These tools perform real-time analytics on local devices without relying on high-speed internet or cloud infrastructure. Such solutions are particularly effective in remote rural settings where connectivity is limited [43, 106]. Mobile applications equipped with embedded ML models, for instance, can diagnose plant diseases offline and suggest treatments based on pre-trained classifiers. This trend democratizes ML access and ensures smallholder inclusivity.

Gender-Inclusive and Ethical AI Frameworks

As ML tools gain traction, future adoption must prioritize ethical AI practices and gender inclusivity. Ensuring that agricultural technologies are co-designed with marginalized communities—including women farmers—can enhance relevance and uptake [107]. Policies promoting transparent data governance, equitable access, and cultural sensitivity will be critical for sustained technological integration.

Roadmap for ML Adoption (2025–2030)

The roadmap for Machine Learning (ML) adoption in Sub-Saharan African (SSA) agriculture outlines a phased implementation strategy spanning 2025-2030 (Figure 9). The phased approach ensures a systematic progression from foundational development to scaling and policy integration.

The initial phase (2025) focused on establishing a strong foundation through comprehensive needs assessments and multi-stakeholder partnerships. This phase successfully completed a baseline assessment of agricultural ML readiness across SSA. The subsequent phase (2025-2026) developed critical infrastructure, including rural connectivity solutions and solar-powered infrastructure, resulting in the establishment of the first regional agricultural technology hub.

Data collection and management (2026-2027) were pivotal in creating standardized frameworks and SSA-specific agricultural datasets. The release of the first comprehensive SSA agricultural ML dataset marked a significant milestone. Capacity building (2027-2028) through specialized ML training programs and partnerships with universities yielded promising results, with 1,000 ML engineers trained in agricultural applications.

The solution development phase (2028-2029) successfully implemented localized ML models and mobile applications with offline capabilities, achieving successful ML implementation across five SSA countries. Finally, the scale and policy integration phase (2029-2030), is expected to document continent-wide impact with measurable agricultural productivity improvements, establishing policy frameworks and sustainable funding models. This phased implementation strategy demonstrates the potential for ML adoption to transform SSA agriculture, with each phase building on the successes of the previous one.

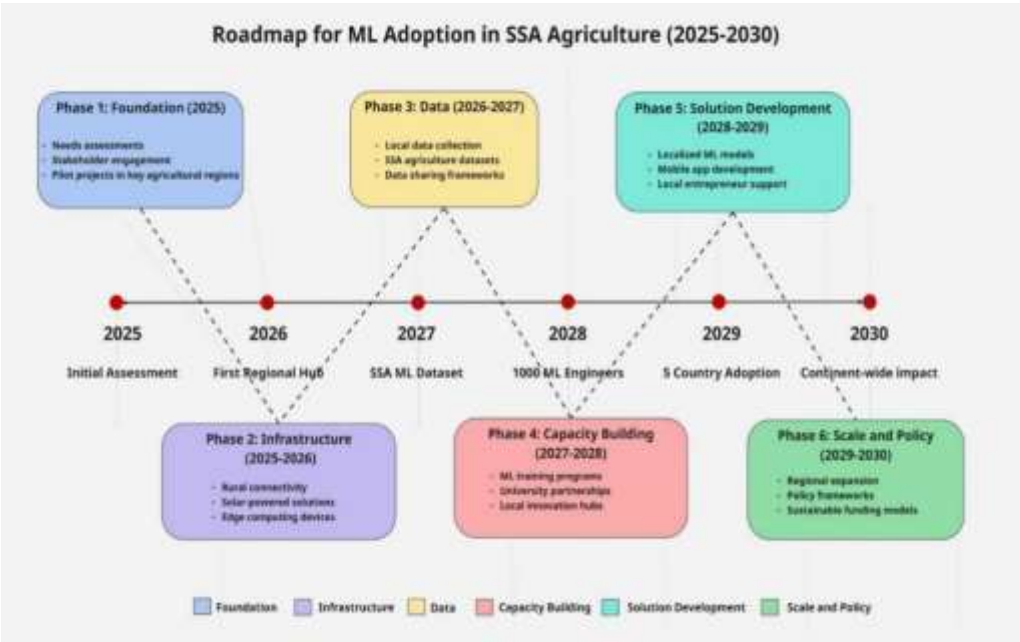

Figure 9. Roadmap for ML Adoption in SSA Agriculture (2025–2030) [84].

CONCLUSION

Machine learning (ML) stands at the forefront of a transformative shift in crop protection and agricultural productivity across Sub-Saharan Africa (SSA). This review has highlighted how ML-enabled tools, such as SMART-CYPS for yield prediction, convolutional neural networks (CNNs) for early disease detection, and intelligent multi-agent irrigation systems, are already reshaping traditional agricultural practices. These innovations have not only improved real-time decision-making capabilities but have also reduced resource inefficiencies and minimized production losses, providing a blueprint for sustainable and climate-resilient farming systems in the region.

However, the adoption and scalability of these technologies remain constrained by several interrelated challenges. Infrastructural barriers such as unreliable power supply, limited internet penetration, and inadequate sensor deployment continue to obstruct digital transformation efforts. Furthermore, issues surrounding data scarcity, low digital literacy among farmers, gender disparities, and socio-cultural resistance to new technologies underscore the need for a more inclusive approach to ML deployment.

Overcoming these barriers will require robust, cross-sectoral collaboration. Governments, research institutions, private-sector actors, and development organizations must work in tandem to enhance infrastructure, promote digital literacy, and tailor ML solutions to the unique agronomic and socio-economic contexts of SSA. Investment in locally relevant data collection and model development is also crucial to improve the accuracy, adaptability, and uptake of ML applications across diverse agro-ecological zones.

CALL TO ACTION

As ML technologies like AI-enabled weed detection, pest monitoring using CNNs and drone imagery, and mobile-based crop advisory platforms continue to evolve, it is imperative that SSA's agricultural transformation does not become a tale of technological exclusion. Future research must prioritize context-aware, low-cost, and interpretable ML models, while also exploring participatory design methods that embed farmer knowledge and local realities into digital solutions.

Ultimately, the potential of ML in revolutionizing SSA agriculture is no longer speculative—it is tangible, evidence-based, and within reach. But to fully harness this potential, there is an urgent need for deliberate policy action, inclusive innovation frameworks, and strategic investment. Only then can machine learning serve not just as a tool for productivity, but as a catalyst for food security, economic empowerment, and sustainable development across the African continent.

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