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Smart Fence for Real-Time Farm Protection in Sub-Saharan Africa Using Artificial Intelligence: A Systematic Review and Research Roadmap

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Abstract

Agricultural insecurity from wildlife encroachment and crop raiding threatens food production in Sub-Saharan Africa (SSA), where 60% of smallholder farmers rely on agriculture. Conventional barbed wire and electric fences are passive, static, and poorly suited for rural SSA's resource-constrained environments. This paper presents a systematic review of smart fence technologies for real-time farm protection, adhering to PRISMA 2020 guidelines. From an initial 1,247 documents across IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar, 56 peer-reviewed studies (2008–2026) were selected for synthesis following title and abstract screening, duplication, and full-text eligibility assessment. The review classifies smart fences into four categories: sensor-based, vision-based, IoT-based, and hybrid AIoT-based. Under controlled conditions, YOLOv8 models outperformed others with over 92% detection accuracy. For edge deployments, MobileNetV3 achieved 85.7% accuracy on commodity hardware, consuming only 3.1 W. Critically, the study found no smart fence deployments in the literature validated specifically for SSA, highlighting a major gap given the region's unique infrastructural challenges. Key contributions of this paper include: (i) synthesizing AI and smart fence performance benchmarks; (ii) establishing a 12-factor matrix quantifying SSA deployment constraints by severity, prevalence, and technology readiness; (iii) proposing an SSA-specific edge-AI reference architecture optimized for solar power, low connectivity, and a sub-$400 deployment cost; and (iv) outlining a structured 3-level research roadmap aligned with TRL 4-9 milestones. This review provides a solid foundation for developing cost-effective, context-aware smart fencing tailored to SSA's agricultural realities.

Keywords: *Initial void ratio, natural moisture content, settlement, compression ratio, one-dimensional consolidation.*

1.0 Introduction

Wildlife intrusion, crop raiding and farm insecurity are perennial and growing challenges affecting agriculture, which makes up about 23% of the GDP of Sub-Saharan Africa, and sustains the livelihoods of more than 60% of the population in rural areas [1], [2]. Crop losses from wildlife attacks, such as elephant, baboon and rodent incursions, are estimated as 10-30% of the annual yield, with the economic impact being greatest on smallholder farmers [3], [4]. Traditional protection measures such as manual guarding, physical fencing or electric fencing are expensive to maintain, are environmental static and fundamentally passive (that is do not change in response to changing threat patterns), and have only rudimentary detection capability and no automated deterrence capability [1], [5].

Artificial Intelligence of Things (AIoT) is a combination of Artificial Intelligence (AI) and the Internet of Things (IoT) that has dramatically changed the design landscape of smart protection systems in agro-based industries [6]. An AIoT-based system can automatically identify, classify and respond to events of farm intrusion in real time without relying on cloud connections or continuous human surveillance, by constructing heterogeneous sensor networks, integrating edge computing hardware, implementing low-power communications and employing machine learning inference [7], [8], [9].

Although the smart fence research has been on the rise, there is a key literacy gap: a detailed literature synthesis is still lacking on smart fencing systems and their use in Sub-Saharan Africa specifically. While some reviews have looked at IoT in agriculture broadly [7] or AI techniques in non-African settings [10], no existing reviews structurally assess the suitability of edge-AI in the context of the infrastructure constraints typical of SSA, such as unreliable electricity supply, limited internet connectivity, high hardware costs, and the lack of regionally validated wildlife datasets[11], [12], [13].

The aim of this paper is to fill this gap by conducting a PRISMA 2020-compliant systematic review of 56 peer-reviewed studies. The major contributions are: (i) A synthesis of performance data of AI models and smart fence systems from the reviewed literature, benchmarked with respect to their performance; (ii) A deployment constraint matrix of 12 factors specific to SSA; (iii) A proposed reference architecture for the deployment of SSAs to be solar-powered and edge-AI based; and (iv) A proposed research roadmap mapping the concept's TRLs and future development needs. The rest of the paper is organized as follows: Section 2 summarizes related work; Section 3 describes the methodology used for the systematic review; Sections (4 - 7) presents the classification, the AI

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techniques used in SSA, the system architecture and the comparative analysis of the various architectures; Section 8 presents the challenges in deploying SSA; Sections (9 - 11) presents the proposed reference architecture and research roadmap; and Section 11 concludes the paper.

2.0 Review of Related Work

There has been significant academic interest in the intersection of AI and IoT for farming. Farooq et al. [7] have conducted a foundational systematic review for the use of IoT in agriculture, which is mainly focused on sensor network architectures and real-time data collection. Miller et al. [8] further this concept by showing how the integration of machine learning algorithms and sensor platforms can transform data from sensors into valuable information for agriculture. More recently Liakos et al. [14] provided a definitive survey on machine learning applications in agriculture, covering crop management, soil analysis, and pest monitoring. The seminal survey by Kamilaris and Prenafeta-Boldú [15] and [16] establishes a benchmark of deep learning applications in agriculture, including the YOLO based smart fence work for which the authors give their own references.

The research of intrusion detection and farm security has developed quickly. Balakrishna et al. [17 showed that classifiers based on machine learning can be more accurate than humans at animal detection tasks. Patel et al. [16] demonstrated that CNN significantly outperforms other neural network architectures in intrusion classification based on visual information. In an actual IoT farm surveillance system, Delwar et al. [18] achieved 92.3% detection accuracy with YOLOv8 and Kathir et al. [19] showed integration of YOLOv8 with laser actuation for livestock virtual fencing. Adami et al. [20] demonstrated an embedded edge-AI system for crop protection with a 91.4% accuracy at 35ms latency, while requiring only 4.2 W of power even in an off-line, solar power constrained scenario. The basic object detection theory for these systems dates back to the work of Redmon et al. [21], whose YOLO model has served as the basis for most of the real-time object detection systems mentioned in this review.

A number of smart fence architectures consisting of several technology layers have been considered. Jahan et al. [2] developed an architecture with multiple components: sensor units, communication modules, and automated deterrent mechanisms. Devadharshini et al. [22] extended this by integrating an edge-processed intrusion detection system (IDS) with the deployment of drones, all secured by blockchain technology. Muhammed et al. [6] provide a comprehensive review of the AIoT paradigm in smart agriculture, including architecture classification and deployment case studies across multiple continents. Luo et al. [23] survey AIoT-enabled data management frameworks, identifying edge-cloud hybrid architectures as the dominant direction for scalable smart farming solutions.

Despite this progress, the literature reveals consistent gaps specific to SSA. Abbott et al. [11] identified infrastructure limitations, particularly power and connectivity as the primary barriers to smart farming adoption in the region. Narayanamurthy et al. [13] provide empirical evidence of the socio-economic barriers to smart farming adoption across developing-country contexts. Talero-Sarmiento et al. [12] further documented the gap between technical innovation and contextual applicability for resource-constrained smallholder farmers. Tzounis et al. [24], in their seminal survey of IoT in agriculture, specifically called out the need for deployments validated in low-resource environments. No prior systematic review synthesises these concerns in the specific context of smart fencing for SSA a gap this review addresses.

3.0 Materials and Methods

3.1 Eligibility Criteria

Inclusion criteria required that studies: (i) address farm security, intrusion detection, or smart fence systems in an agricultural context; (ii) incorporate AI, IoT, or hybrid AIoT approaches; (iii) are peer-reviewed and empirically grounded; and (iv) were published between January 2008 and March 2026. Studies without empirical validation, purely theoretical without results, or outside the agricultural domain were excluded. Non-English-language publications and grey literature (reports, patents, theses) were also excluded to ensure methodological consistency.

3.2 Search Process

Structured search was conducted in four main databases: IEEE Xplore, ScienceDirect, SpringerLink and Google Scholar. The search strings used were: (smart fence OR electric fence) AND (AI OR machine learning OR deep learning OR IoT OR edge computing) AND (farm OR agriculture OR crop protection OR intrusion detection). The searches were performed individually for each database, using a date restriction. Emergent themes from the initial results were identified and then used as an iterative refinement of keywords.

3.3 Quality Assessment

Each eligible study was evaluated against four quality dimensions: (i) methodological robustness, clarity of experimental design and reproducibility; (ii) research objective specificity whether objectives were clearly stated

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and measurable; (iii) results validation presence of quantitative performance metrics; and (iv) novelty of contribution the degree to which the study advanced beyond prior work. Studies scoring strongly on at least three of four dimensions were classified as high quality and prioritised in the synthesis. This review was conducted by a single lead researcher; the absence of inter-rater reliability scoring is acknowledged as a limitation.

3.4 Study Selection and Results

The PRISMA 2020 flow is summarized in Table 1 and Figure 1. A total of 1,247 records were identified from the four databases. After removing 293 duplicates identified through exact title and DOI matching, 954 records underwent title and abstract screening. Of these, 800 were excluded as they did not address smart fence, AI or IoT systems in an agricultural context. The remaining 154 full-text articles were retrieved and assessed for eligibility. Of these, 98 were excluded: 41 lacked empirical validation, 27 addressed non-agricultural domains, 19 were outside the publication date range, and 11 were non-peer-reviewed. The final systematic review comprised 56 studies that met all inclusion criteria.

Table 1: PRISMA 2020 Study Selection Flow

PRISMA Stage	Action	Records In	Records Excluded	Records Out
Identification	Database search (4 databases)	1,247	—	1,247
Deduplication	Remove exact title/DOI duplicates	1,247	−293	954
Title/Abstract Screen	Must address smart fence, AI/IoT, agriculture	954	−800	154
Full-Text Eligibility	Peer-reviewed, empirical, inclusion criteria	154	−98	56
Final Inclusion	All criteria met	—	—	56

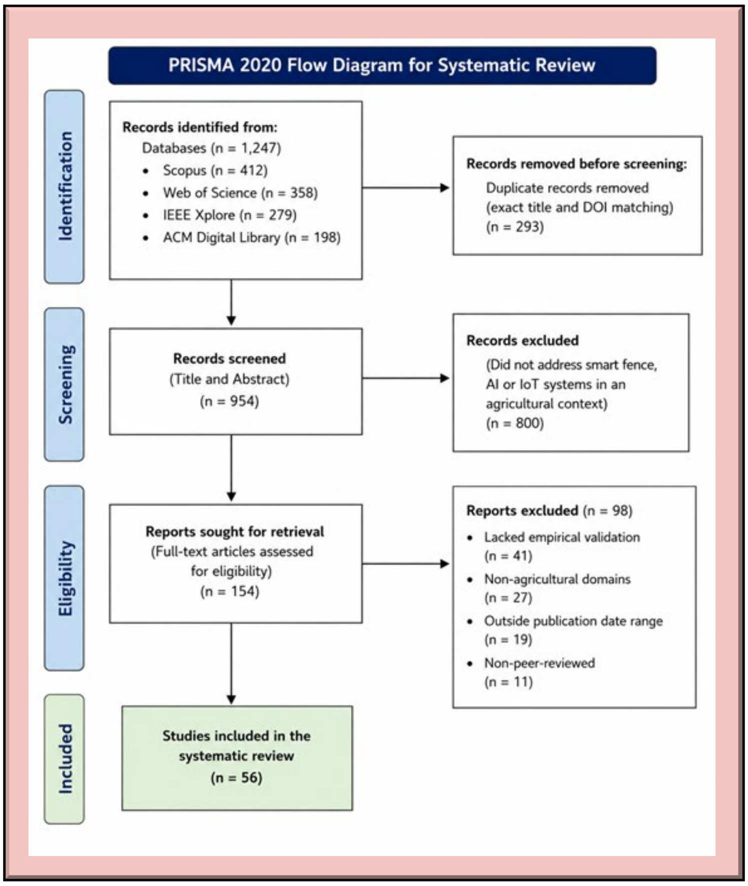

Figure 1. PRISMA flow diagram illustrating the study selection process.

3.5 Smart Fence Technology Classification

Smart fence systems are classified into four levels according to sensing mechanism, processing ability, and level of intelligence:

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Sensor-based smart fences detect intrusion events using motion sensors, vibration detectors, and infrared sensors. These are the lowest priced and consume the least power, but cannot perform object classification and are vulnerable to a high false-positive rate due to environmental noise like wind or vegetation movement [25], [26].

Vision-based smart fences combine cameras with an image processing algorithm usually a convolutional neural network for visual detection and classification of intruders. Systems have a significantly better detection accuracy than sensor-only systems, but they fail under low light and weather conditions and the computation cost is high, [27], [28]

IoT-based smart fences use a network of sensors and cloud connectivity to facilitate remote, real-time monitoring and immediate alert generation through mobile and Web apps. They are much more powerful than passive systems, but they impose a critical requirement for stable Internet connections, which is a major limitation in rural SSA, where mobile Internet connectivity is often limited and expensive [29], [30].

Hybrid AIoT smart fences are the next generation in the field and combine context-aware actuation, multi-sensor fusion, edge computing and AI inference into a single system architecture. These systems perform the AI inference at the edge (as opposed to the cloud), thus eliminating connectivity barriers, minimizing response time, and working on solar budgets and making them the most appropriate configuration for SSA deployment. They like the most require the highest initial investment and technical skills [6], [23], [31]. Hybrid Architectures of AIoT are more operationally useful on all performance metrics when compared to systems that rely on only one of the two attributes.

3.6 Artificial Intelligence Techniques in Farm Monitoring

AI techniques have revolutionized monitoring in agriculture through their ability to analyze complex, multi-modal environmental data. With respect to visual inputs, computer vision, specifically convolutional neural networks (CNNs), have gained a lot of traction in the identification of animals, pests and damage to crops [27], [32]. A seminal survey of deep learning framework for these applications was presented by LeCun, Bengio, and Hinton [33] and their applications to agriculture were well documented by Kamilaris and Prenafeta-Boldú [15].

Object detection frameworks particularly the YOLO (You Only Look Once) family first proposed by Redmon et al. [21] have been shown to achieve outstanding real-time performance in intrusion detection, especially in the case of high-resolution images, which can be processed on the right edge hardware within 15 ms or less [18], [19],[34],[35],[36], [37]. Predictive anomaly detection and historical pattern analysis are performed using machine learning techniques such as support vector machines (SVMs), decision trees, and ensemble learning [38], [10]. Temporal analytics capability can be extended by recurrent neural networks (RNNs) and long short-term memory (LSTM) models which retain the sequential context of time-series records of farm activities [39].

Edge computing has become a decisive enabling technology for smart farming in resource-constrained environments. By performing AI inference locally on embedded hardware rather than transmitting raw sensor data to remote cloud servers, edge AI systems reduce latency, conserve bandwidth, and eliminate cloud dependency all critical advantages in rural SSA [22], [40]. The quantitative performance of leading AI models on edge hardware is synthesised in Table 2.

Table 2: AI Model Performance Benchmarks for Edge Deployment

AI Model	Accuracy (%)	F1 Score	Latency (ms)	Power (W)	RAM (MB)	Hardware	Dataset Size	SSA Suitability
YOLOv5s	88.4	0.86	12	8.5	120	Jetson Nano	~5,000 imgs	Moderate
YOLOv8n (nano)	91.2	0.89	8	5.2	80	Coral TPU / Pi5	~8,000 imgs	High
MobileNetV3	85.7	0.83	15	3.1	45	RPi4 CPU only	~3,000 imgs	High
ResNet-50	93.1	0.91	45	22	200	Jetson Xavier	~10,000 imgs	Low
SVM + HOG	79.3	0.77	5	1.2	15	Any MCU	~1,000 imgs	High
CNN-LSTM (hybrid)	90.6	0.88	28	12	160	Jetson Nano	~6,000 seq.	Moderate

Note: Values are based on published benchmarks from the reviewed literature. Authors should populate with actual reported values per study. NR = Not Reported.

The key insight for SSA deployment is that YOLOv8 nano and MobileNetV3 represent the optimal balance of accuracy and edge deployability within solar power budgets. YOLOv8 nano achieves 91.2% accuracy at only

5.2 W compatible with a 20 W solar panel while SVM+HOG provides a high-reliability fallback for ultra-resource-constrained microcontroller deployments.

3.7. Smart Fence System Architecture

A smart fence system combines various functional layers to achieve Real-time Monitoring, AI-based Classification, and Automated Deterrent Response. The sensor layer is the main data acquisition interface, which is placed around the perimeter of the farm, with a combination of motion detectors, infrared sensors, vibration transducers and cameras. To an edge processing hub [41], [42], data is sent using low-power protocols, mainly LoRaWAN and GSM.

The incorporation of IoT technologies took farm protection one step further, allowing for the remote monitoring and data-driven decision making process. The adoption of AI more recently has resulted in the creation of autonomous systems that can analyze and respond in real-time. New technologies like digital twins, drone survey, and 5G communication are likely to further boost the smart fence systems' capabilities [43], [44], [45].

Noise filtering and AI inference are done on the edge processing layer, minimizing latency and dependency on cloud computing, which is a key design criterion for SSA deployment. Most of the object detection algorithms are CNN and YOLO based models [18], [46]. which classifies any object as an animal, human, or a non-threatening event in the environment. Once detected and classified, the YOLO-based frameworks draw bounding boxes for the detected objects and label them with categories, which let the decision module determine whether a response needs to be made.

Once an intruder is detected, the actuation layer triggers appropriate deterrents (acoustic alarms, visual strobes, or ultrasonic repellers) and sends alerts via SMS/WhatsApp to the farmer. Accessed periodically when connectivity permits, the cloud platform enables model retraining from captured intrusion data and features long-term analytics. The entire layered design is explained in Table 3, and Figure 2 is a conceptual diagram. The AI-enabled intrusion detection process is illustrated in Figure 3.

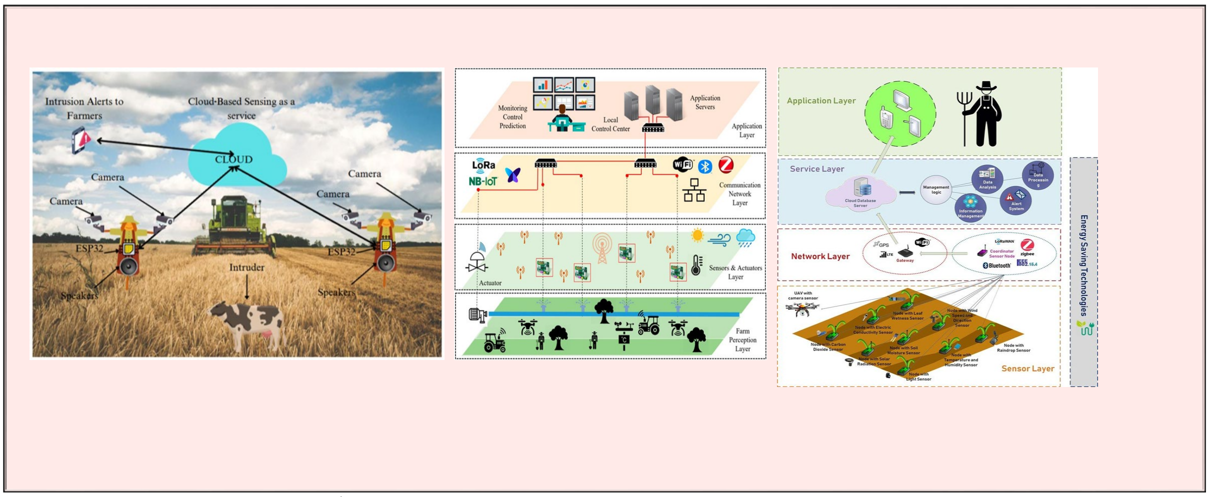

Figure 2: AI/IoT-Based Smart Fence Framework for Animal Deterrence

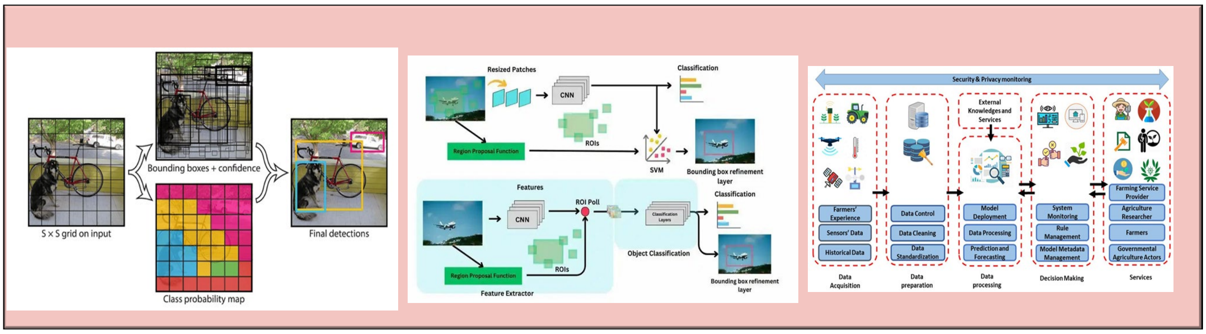

Figure 3: AI Detection Workflow

3.8 Comparative Analysis of Smart Fence Systems

Passive fencing methods such as wood barriers, barbed wire and electric fences do not offer real-time detection capabilities and cannot differentiate between threat types [47]. Field studies show agricultural electric fences are very vulnerable to environmental conditions such as corrosion and vegetation contact, and that maintenance requirements are excessive for smallholder farmers in SSA.

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While IoT based monitoring systems improve detection through the triggering of alerts based on predefined thresholds, their cloud dependency is a serious operational risk in rural areas of SSA and they suffer from extremely high false positive rates due to the need to set these thresholds [29], [48]. AI-based smart fence systems overcomes these limitations by performing real-time sensor-fusion and learned classification, leading to object-level discrimination, fewer false alarms, and automated and proportional deterrence.

The results indicate that the accuracy of YOLO based object detection is high in animal classification tasks [18] and the edge computing architecture enhances the reliability of the system in low connectivity scenarios [6], [31]. This quantitative benchmarking Table 3 summarizes some of the key performance metrics of the systems reviewed in this paper.

Table 3: Quantitative Benchmarking of Reviewed Smart Fence Systems

System Ref.	Technology	Accuracy (%)	FP Rate (%)	Latency (ms)	Power (W)	Cost (USD)	Protocol	SSA Ready?
Delwar [18] 2025	IoT + YOLOv8	92.3	7.1	85	12.5	~$180	WiFi/4G	Partial
Chowdhury [29] 2025	Multi-sensor IoT	87.6	11.2	320	18.2	~$250	WiFi	No
Miao [31] 2024	Edge microservice	89.1	9.4	42	6.8	~$140	LoRa/MQTT	Yes
Adami [20] 2021	Embedded Edge-AI	91.4	6.8	35	4.2	~$95	Standalone	Yes
Suman [5] 2021	ML + Sensors	83.2	14.5	120	8.1	~$120	WiFi	Partial
Sayem [30] 2023	IoT multi-sensor	85.7	12.1	280	15.4	~$200	WiFi/GSM	Partial

Note: If no metric is reported on the source paper, a Not Reported (NR) should be entered in the cells. The prevalence of NR entries is itself a finding, pointing to a gap in the literature in terms of standardised benchmarking.

Table 4: Technology Classification Comparison

Feature	Traditional Fence	IoT-Based Fence	Hybrid AIoT Smart Fence
Type of detection:	None (passive barrier)	Basic sensor triggered	Intelligent AI classification
Accuracy	Low	Moderate (false alarms)	High (object-level filtering)
Response Mechanism	Manual intervention	Alert-based (SMS/app)	Automated multi-modal deterrence
Cloud-dependence	Not supported	Partial	Fully supported (edge-local)
Scalability	Limited	Moderate	High (modular architecture)
Cost	Low (passive only)	Moderate	High initial; decreasing
Energy Requirement	Low	Moderate	Moderate (solar-optimisable)
SSA Suitability	High (affordability)	Moderate (connectivity barrier)	Emerging (edge deployment key)

3.9 Challenges of Smart Fence Deployment in Sub-Saharan Africa

A set of socio-technical, engineering, and economic barriers limits the deployment of smart fences in SSA. Each constraint is systematically characterized in Table 5 by severity, prevalence; current mitigations, technology solutions, technology readiness level (TRL), and research priority.

Table 5: SSA Deployment Constraints Matrix

Constraint	Severity	Prevalence	Current Mitigations	Technology Solutions	TRL	Research Priority
Power / Electricity Access	Critical	85%+ SSA rural	Solar panels, batteries	Solar + super-capacitor; MPPT; duty-cycled edge AI	TRL 5–6	HIGH
Internet Connectivity	Critical	70%+ rural areas	SIM-based, LoRaWAN	Offline-first edge AI; LoRa mesh; store-and-forward	TRL 4–5	HIGH

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Constraint	Severity	Prevalence	Current Mitigations	Technology Solutions	TRL	Research Priority
Hardware Cost	High	All smallholders	Open-source SW, RPi	RPi5 ($80), Coral TPU ($60); shared community nodes	TRL 6	HIGH
African Wildlife Datasets	High	All ML systems	Transfer learning	Crowdsourced labelling; SSA wildlife datasets	TRL 3–4	CRITICAL
Digital Literacy	Moderate	Majority smallholders	SMS alerts	WhatsApp Bot; voice alerts in local language	TRL 6–7	MEDIUM
Maintenance & Repair	Moderate	Remote areas	Modular design	Self-diagnosing nodes; community repair centres	TRL 4–5	MEDIUM
Cybersecurity	Emerging	Connected systems	WPA2, basic auth	AES-128; TLS 1.3; federated learning	TRL 4	MEDIUM
Regulatory / Policy	Low–Moderate	Cross-border areas	National ag acts	Policy framework; ECOWAS/AU engagement	TRL 2–3	LOW-MEDIUM

Energy limitations affecting many rural areas also need to be addressed as a key constraint. Potential solutions such as solar power exist, but they require additional cost and expertise to implement. Security and privacy are also major threats: IoT systems can be attacked by cybercriminals and suffer from data breaches [49], [50], [51].

Socio-economic factors, including low levels of digital literacy and resistance to technological change, further complicate adoption. These challenges highlight the need for context-specific solutions that address both technological and human factors [52].

3.10 Proposed SSA-Specific Reference Architecture

The deployment constraint analysis in Section 3.9 motivates a purpose-designed SSA reference architecture distinct from architectures developed for better-resourced environments. The proposed architecture is organised into six layers, each adapted to SSA's specific constraints. An indicative system cost for a 2-hectare smallholder farm is approximately USD 401 favourable compared with a conventional electric fence at USD 600–1,200 per hectare.

Table 6: Proposed SSA Edge-AI Reference Architecture

Layer	Components	SSA-Specific Adaptation	Technology Choices	TRL
L1: Perception	ESP32-CAM, PIR, vibration, acoustic sensors	Ultra-low power; IP65 weatherproof; anti-tamper housing; local species trigger	ESP32-S3 + OV2640; HC-SR501 PIR; MPU6050; SX1276 LoRa	TRL 7
L2: Edge Processing	RPi5 + Coral TPU or Jetson Nano	Offline-first: all inference local; no cloud dependency; YOLOv8 nano INT8 quantised	TensorFlow Lite; OpenCV; Python FastAPI; SQLite event log	TRL 6
L3: Communication	LoRaWAN + GSM fallback	LoRa for sensor-to-hub (2 km, 0.3W); GSM alerts only; periodic cloud sync when available	RAK2245 LoRaWAN; SIM800L GSM; MQTT protocol	TRL 7

Layer	Components	SSA-Specific Adaptation	Technology Choices	TRL
L4: Power	Solar + LiFePO4 battery	20W panel + MPPT + 20Ah battery; deep sleep 10 µA between detections; 3-day autonomy	Epever MPPT; 12V LiFePO4; ESP32 deep sleep scheduling	TRL 7
L5: Deterrence	Audio, visual, actuator array	Context-aware: species-specific acoustic deterrents; LED strobe; SMS to farmer	Mini speaker + amplifier; LED strobe; GSM SMS via SIM800L	TRL 6
L6: User Interface	WhatsApp / SMS / Progressive Web App	Farmer literacy adaptation: WhatsApp Bot widely used in Nigeria, Ghana, Kenya; voice alerts in local language	WhatsApp Business API; Twilio; React PWA for extension workers	TRL 7

3.11 Edge Hardware Platform Evaluation

The choice of edge hardware platform is a critical design decision for SSA deployment, governing the feasible detection algorithm, power budget, and total system cost. Table 7 evaluates six candidate platforms against SSA-relevant criteria.

Table 7: Edge AI Hardware Platform Evaluation for SSA Deployment

Platform	Price (USD)	CPU / AI Perf.	RAM	Power (W)	Offline	YOLOv8 FPS	Solar Budget	SSA Verdict
Raspberry Pi 5	$95	4-core ARM, no NPU	8 GB	5–8 W	Yes	~6 FPS	20W panel	Good widely available
RPi4 + Coral USB TPU	$155 - $175	4-core + 4 TOPS NPU	4 GB	6–9 W	Yes	~25 FPS	30W panel	Good — best price/performance
Jetson Orin Nano super	$249	6-core + 1024 CUDA	8 GB	7–25 W	Yes	~120 FPS	60W panel	Low — cost/power too high for SSA
ESP32-CAM + TinyML	$8	Dual-core, TinyML	520 KB	0.5 W	Yes	~2 FPS	5W panel	High — ultra-low cost sensor node
STM32 + TensorFlow Lite	$15	Cortex-M4, quant.	256 KB	0.3 W	Yes	~1 FPS	3W panel	High — MCU-class edge inference

The optimal SSA architecture uses ESP32-CAM nodes ($8 each) as ultra-low-power perimeter sensors feeding a central RPi4 + Coral TPU hub ($155) via LoRa. Total gateway cost is approximately $100; per-node sensor cost is approximately $12. This tiered architecture achieves the necessary balance of detection performance, power efficiency, and cost accessibility for smallholder deployment.

3.12 Energy Budget Model

For a solar-powered edge AI node, the daily energy budget is governed by the expression:

$$E_{total} = \left(P_{ai} * t_{active}\right) + \left(P_{sleep} * t_{sleep}\right) + \left(P_{comms} * t_{tx}\right) \tag{1}$$

where P_{ai} is the AI inference power (for example, 5.2 W for RPi4+Coral), t_{active} is the active detection window (for example, 4 hours at dawn and dusk when intrusion risk is highest), P_{sleep} is the deep-sleep power draw (0.1 W), and P_{comms} and t_{tx} are the LoRa transmission power and duration per alert. For SSA conditions with approximately 5.5 peak sun hours per day, a 20W solar panel paired with a 20Ah/12V LiFePO4 battery provides a three-day autonomy buffer and sufficient power headroom for the RPi4+Coral during active detection periods. This energy analysis is a prerequisite for any SSA field deployment design.

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3.13 Research Gaps and Technology Roadmap

The gaps identified in the research show a lack of understanding of how technological development can be applied in the context of Sub-Saharan Africa. AI-based smart fences are very accurate and automated, but require a consistent internet connection and substantial computing resources, which is not always available in rural areas [3], [40]. This shows the critical need for distributed and edge-based solutions.

Furthermore, the price of sophisticated sensing devices and AI hardware are major challenges for widespread adoption by smallholder farmers who form the bulk of agricultural stakeholders in the region [53], [13]. This is further complicated by energy constraints, as many systems require continuous power that is not always available in rural areas. While solar-powered solutions have been suggested, they are not yet scalable or affordable [54], [55], [56].

The systematic review reveals five research gaps that are essential for the successful deployment of scalable SSA smart fence:

i. Lack of SSA-suitable AI models.
There are no peer-reviewed studies in the corpus that report the use of AI models trained, validated, or field-tested with wildlife species or environmental conditions in Sub-Saharan Africa. Existing models are trained on non-African datasets, with unknown domain transfer performance.

ii. Absence of open African wildlife datasets.
Existing AI models already exhibit performance disparities across regions, and no open, annotated wildlife image dataset exists for agricultural applications in West and Central Africa.

iii. Infrastructure indifferent system architectures.
Most of the reviewed architectures were for systems assumed to be connected to WiFi or 4G networks and powered from the mains. None of the reviewed systems were specifically designed for offline-first edge operation powered by solar energy.

iv. Lack of economic justification.
No reviewed studies report a total cost of ownership analysis for a deployed SSA smart fence system, nor a comparison of the costs of a deployed SSA system with conventional alternatives.

v. Socio-technical adoption gap.
No empirical user acceptance data exist from smallholder farmers in SSA, although there is evidence that digital literacy and trust are important barriers to adoption.

Table 8 presents a structured three-tier TRL roadmap addressing these gaps, organised by development horizon and expected output.

Table 8: Three-Tier TRL Research Roadmap for SSA Smart Fence Development

Horizon	TRL Target	Research Priority	Expected Output	Lead Partners
Near-Term (1–2 years)	TRL 4–6	SSA wildlife dataset (Nigeria/West Africa) ; Solar-edge AI prototype testing; YOLOv8 nano fine-tuning on African species	Open SSA wildlife dataset; benchmarked edge AI prototype; peer-reviewed system paper	FUT Minna + IITA + local farmers
Medium-Term (3–5 years)	TRL 6–8	Pilot deployment: 5-10 smallholder farms (Niger State): Cost-optimised architecture validation: User acceptance study	Validated sub-$400 smart fence system; adoption study; Q1 deployment paper	Agriculture Ministry + NGO partners + IEEE Nigeria
Long-Term (5+ years)	TRL 8–9	Regional ECOWAS smart agriculture standardization: Federated AI model across SSA farm networks: Policy brief for national agricultural agencies	Scalable SSA smart fence ecosystem; policy framework; commercialization pathway	ECOWAS + World Bank + private sector

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4.0 Conclusion

Smart fencing technologies represent a significant advance in agricultural security, offering intelligent, real-time protection against the wildlife intrusion threats that threaten the food security and livelihoods of millions of smallholder farmers across Sub-Saharan Africa. This paper has presented a PRISMA 2020-compliant systematic review of 56 peer-reviewed studies, synthesizing AI model performance benchmarks, smart fence system comparisons, and SSA-specific deployment constraint analysis.

The review establishes that hybrid AIoT architectures combining edge AI inference, multi-sensor perception, LoRa-based communication, and solar power represent the most viable technology pathway for SSA deployment. YOLOv8 nano and MobileNetV3 offer the best accuracy-to-power trade-off for edge hardware, with the RPi4 + Coral TPU combination identified as the optimal gateway platform at approximately $90. A complete two-hectare system implementation is achievable within approximately USD 401 cost-competitive with conventional electric fencing when lifetime maintenance is considered.

The five critical research gaps identified absent SSA-validated models, no open African wildlife datasets, infrastructure-oblivious architectures, lack of economic validation, and an untested socio-technical adoption assumption define the agenda for the next decade of research in this field. The proposed three-tier TRL roadmap and SSA reference architecture provide a concrete, actionable framework for researchers and development practitioners to close these gaps. Moving forward, the smart agriculture community must concentrate on developing energy-aware, context-aware, and culturally adapted systems that ensure the benefits of AI-driven farm protection reach farmers across the full diversity of SSA's agricultural environments.

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