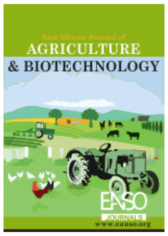

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Original Article

The Role of Artificial Intelligence in Livestock Farming for Improved Animal Health and Productivity: Opportunities, Challenges, and Future Research Directions

Alcardo Alex Barakabitze[1] & Camilius Sanga[1]*

[1] Sokoine University, P. O. Box 3000, Morogoro, Tanzania.
[*] Author for Correspondence, Email: alcardo.alex@sua.ac.tz

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Smart Farming, Livestock Farming, Animal Production, Animal Health, Tanzania.

ABSTRACT

Livestock farming is a growing sector globally, and it makes a big contribution to GDP and food security. In Sub-Saharan countries such as Tanzania, livestock farming is used as a means of poverty eradication in some communities, but it requires a lot of manpower, time, and material resources to monitor animal health and welfare. As the number of animal farming enterprises increases, the continued use of traditional livestock monitoring methods may reduce economic outputs and the welfare of animals; thus, farmers are opting for ICT solutions to mitigate this. Machine learning and artificial intelligence (AI) are used to revolutionise how livestock is managed and monitored. Machine learning algorithms are an integral part of precision livestock farming. Farmers can use it to streamline the monitoring of animal behaviour and welfare, predict disease outbreaks, and optimise feeding schedules. This paper aims to assess the role of artificial intelligence technology in animal husbandry to improve animal one health and production. We conducted a systematic literature review from relevant databases. Finding studies showed that AI has a great role in animal husbandry. The studies revealed that AI technology has various uses like health monitoring, reproduction monitoring (oestrus and parturition and pedigree), real-time data collection, automated milking, location tracking, and identification of animals, hence theft prevention, detection of animal parameters, Hatchery condition detection, reducing workload, pasture evaluation, and grazing management. To conclude, we propose an artificial intelligence– based framework for monitoring livestock and increasing animal productivity and sustainability in Tanzania.

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INTRODUCTION

Solutions focusing on the quality of animal care as well as the state of animal welfare are considered effective ways to achieve an optimal and sustainable animal farming. To some extent, it is not easy to achieve good animal welfare (Pereira *et al*., 2018), which covers various conditions of health, safety, behavioural and emotional expression with traditional measures. The emergence of Machine Learning (ML) and Artificial Intelligence (AI) technology has the potential to cope with and improve animal welfare and production performance in animal farming (Alves *et al*., 2021). AI has been successfully adopted by several industries, and now it is set to revolutionise the future of farming with drones, robots, and intelligent monitoring systems. A technique for monitoring the health of farm animals and dairy cattle with a high degree of accuracy uses blockchain technology (Aloyce et al., 2023), a camera and AI to achieve a "smart" cow house. AI for detailed observation, powered image analysis could enable early detection of injuries and illnesses that could impact the quantity and quality of health and production (Andonovic *et al.,* 2018). The application of AI has enabled the emergence of smart livestock farming, driven by technological advancements over the past two decades in areas such as information and communication technologies, the Internet of Things (IoT), wireless communication networks, and the expanded availability of Internet access (Terrasson *et al.,* 2017). ML/AI are transforming livestock management and monitoring, serving as essential components of precision livestock farming while advancing the One Health agenda by promoting animal welfare, safeguarding human health, and ensuring environmental sustainability.

The spread of Precision Livestock Farming (PLF) (Nsabiyeze *et al.,* 2025) has also been significantly aided by developments in engineering and multimedia streaming (Barakabitze et al., 2020; Barakabitze et al.,2023) and biomaterials research, which have reduced the cost of electronics and allowed for the miniaturisation of electronic components (Aquilani *et al.,* 2022). PLF might offer farmers constant, unobtrusive, and objective data gathering that is capable of spotting minute but important changes in behavioural patterns or seemingly unrelated parameters, considerably enhancing farmers' ability to control their decision-making. This kind of farmer support is crucial in pasture-based systems because there is less frequent farmer management over the animals. AI and ML could provide farmers with continuous, non-intrusive, and objective data collection, able to detect small but significant changes in behavioural patterns or apparently unrelated parameters, which greatly improve farmers' decision management (Aquilani *et al.,* 2022). In the last decades, the AI/ML technologies sector has rapidly evolved, from its earlier applications for electronic milk meters to novel wearable sensors and integrated systems capable of detecting an animal's physiological and reproductive status with acceptable reliability through behaviour analysis, rumination monitoring, and online real-time data

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harvesting (Mellor *et al.,* 2015; Ngwira *et al.,* 2024).

The information collected is elaborated and made available to end-users on smartphones and laptops, enabling farmers to put in practice better management of one or more production inputs so as to identify and intervene before the onset of clinical illness (Resti *et al.,* 2024). In Tanzania, there are identified knowledge gaps on digital technology and services available to both large and smallholder farmers and their sustainability in agriculture (Mellor *et al.,* 2015). The various livestock sectors have long used tools to track animal productivity. Today, the dairy, pig, and poultry industries all commonly employ automatic weighing equipment. On contemporary farms, monitoring the production of milk and eggs is likewise a highly automated procedure in developed countries. The use of contemporary technologies to optimise the growth and production of animals through automated feed management, aside from the dairy industry, which is pioneering the field with automated milking systems, is, however, still in its infancy in developing countries like Tanzania. Since normal feeding systems often provide animals with the same amount and composition of feed (e.g., some animals may receive too much and others too few nutrients), feeding management is an intriguing topic in many developing countries.

This paper identifies different applications of AI technology and suggests digital solutions to solve livestock and farmers' challenges towards enabling sustainable agriculture development in developing countries like Tanzania (Barakabitze et al.,2017; Barakabitze et al., 2015). This aligns with the United Nations Sustainable Development Goals (SDGs), such as (a) Goal 1: No poverty, (b) Goal 2: Zero hunger, (c) Goal 3: Good Health and Well-being, (d) Goal 10: Reduced Inequality, and (e) Goal 13: Climate Action (UN SDGs, 2015). Developing new digital comprehensive artefacts could solve the existing problems of digital exclusion of livestock farmers, such as access to veterinary services, farming knowledge and extension services, livestock and fisheries inputs, market for their products, and livestock disease diagnosis. Fig. 1 shows the linking of animal monitoring with management actions in a data-driven framework. The data –driven animal management can monitor the animal's environment, monitor animal bio-response, analyse the effect on productivity, and support the farmer, leading to the improvement of the animal's well-being and health.

Objectives and Contributions

The main objective of this paper is to critically review and synthesise the current applications, opportunities, and challenges of Artificial Intelligence (AI)–based smart livestock farming systems, focusing on their potential to enhance animal identification, health monitoring, body-weight estimation, behaviour analysis, pasture management, herd management, and One Health surveillance**.**

Key Contributions of the Paper

The main contributions of this paper are threefold:

A Comprehensive Synthesis of AI Applications across the Livestock Value Chain

This manuscript provides a detailed and integrated review of the full spectrum of AI technologies currently applied in livestock farming, including computer vision, sensor-based monitoring, RFID systems, walk-over-weigh platforms, GPS/GSM tracking, accelerometer-based behaviour assessment, remote sensing for pasture evaluation, and predictive analytics for disease detection. The study establishes a holistic understanding of how AI can support precision livestock farming (PLF) in Tanzania and similar African contexts by bringing together evidence from various domains (e.g., animal identification, behaviour, reproduction, location tracking, and health monitoring).

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Development of an AI-based Smart Livestock Monitoring Framework

We introduce an integrated AI-enabled monitoring framework that combines environmental sensing, real-time computer vision (RT-DETR), IoT devices, behavioural analytics, and automated control systems. This conceptual framework demonstrates how AI can create continuous, data-driven surveillance systems for livestock management, enabling early detection of abnormal health conditions, automated environmental regulation, and improved animal welfare. This contribution supports the design of smart farms tailored to resource-limited settings in Tanzania.

Identification of Implementation Gaps, Opportunities, and Future Research Directions

The review identifies key barriers to AI adoption, including limited connectivity, insufficient digital infrastructure, high system costs, a lack of standardised datasets, and limited farmer capacity, and highlights priority areas for investment and policy support. We provide future research directions related to predictive disease modelling, automated farm operations, genetic selection, environmental sustainability, and AI-supported decision tools. The paper emphasises the need for government support, private-sector partnerships, and farmer training programs to scale AI-based smart livestock systems in Tanzania.

Research Questions

Four specific research questions have been addressed for this purpose:

- To what extent are current AI technologies (e.g., computer vision, IoT sensors, RFID systems, accelerometer-based behaviour tracking, and remote sensing) being applied across the livestock value chain, and how effectively do they address key functions such as animal identification, health monitoring, body-weight estimation, and pasture management?
- How can an integrated AI-enabled smart livestock monitoring framework that incorporates real-time computer vision (RT-DETR), IoT devices, behavioural analytics, and automated control systems be designed to improve continuous surveillance, early disease detection, and overall herd management efficiency in Tanzanian livestock systems?
- What infrastructural, socio-economic, policy, and technical barriers hinder the adoption and scaling of AI-driven smart livestock farming systems in Tanzania?
- What opportunities and research pathways exist to enhance future development in areas such as predictive disease modelling, One Health surveillance, and automated farm operations?

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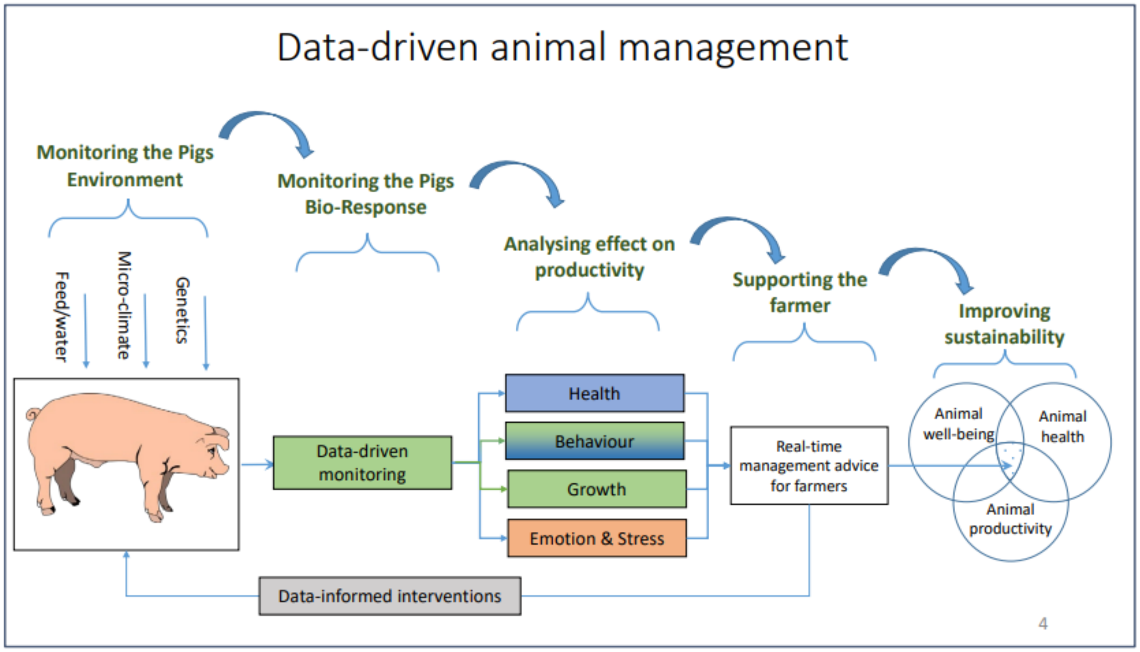
Figure 1: Schematic of the Linking of Animal Monitoring with Management Actions in a Data-Driven Framework



Source: *(Tomas Norton, 2023)*

RESEARCH MATERIAL METHODS

Systematic Review Protocol

To produce a credible and thorough review, the protocol for this systematic literature review (SLR) followed a standard process across the planning, conducting, and discussing phases (Staples & Niazi, 2008). Additionally, the selection criteria were referred to in the review literature (Awan *et al.,* 2021c) and survey (Awan *et al.,* 2021a).

Articles Searching and Selection Criteria

We used the PRISMA guideline in this study review (Kumari & Dhawal, 2021), which is a standard protocol and an evidence-based framework for doing systematic review studies. The cited work must satisfy the following requirements (Awan *et al.,* 2021c) to be taken into account: (1) cover both farm animals and intelligent technology; (2) be published in refereed journals or peer-reviewed conference papers; and (3) present unique and novel research work in the field of AI/ML and animal farming. The inclusive articles that were screened and met the screening criteria were 155 papers.

We conducted an extensive literature search based on a complex query and search strategy, artificial intelligence-based smart livestock farming to improve animal health and production from Web of Science (WOS), IEEE Explore, Google Scholar, Researcher4Life Database, and PubMed articles. We included evidence-based methodology and only focused on studies with quantitative/qualitative research. The aim was to find and review the literature on the role of artificial intelligence in animal husbandry to improve animal health and animal production in livestock farming. The Research combined the following keywords using the Boolean operators (“AND” and “OR”) and parentheses during the search: digital technology AND smart livestock farming, precision livestock farming, digital farmer profiling, and digital pasture-based livestock systems. The final search string was “(‘digital technology’ OR ‘precision livestock farming’ AND ‘smart livestock farming’ OR ‘Digital pasture-based livestock systems’). Figure 2 shows the literature searching process based on keywords related to the parameter of interest.

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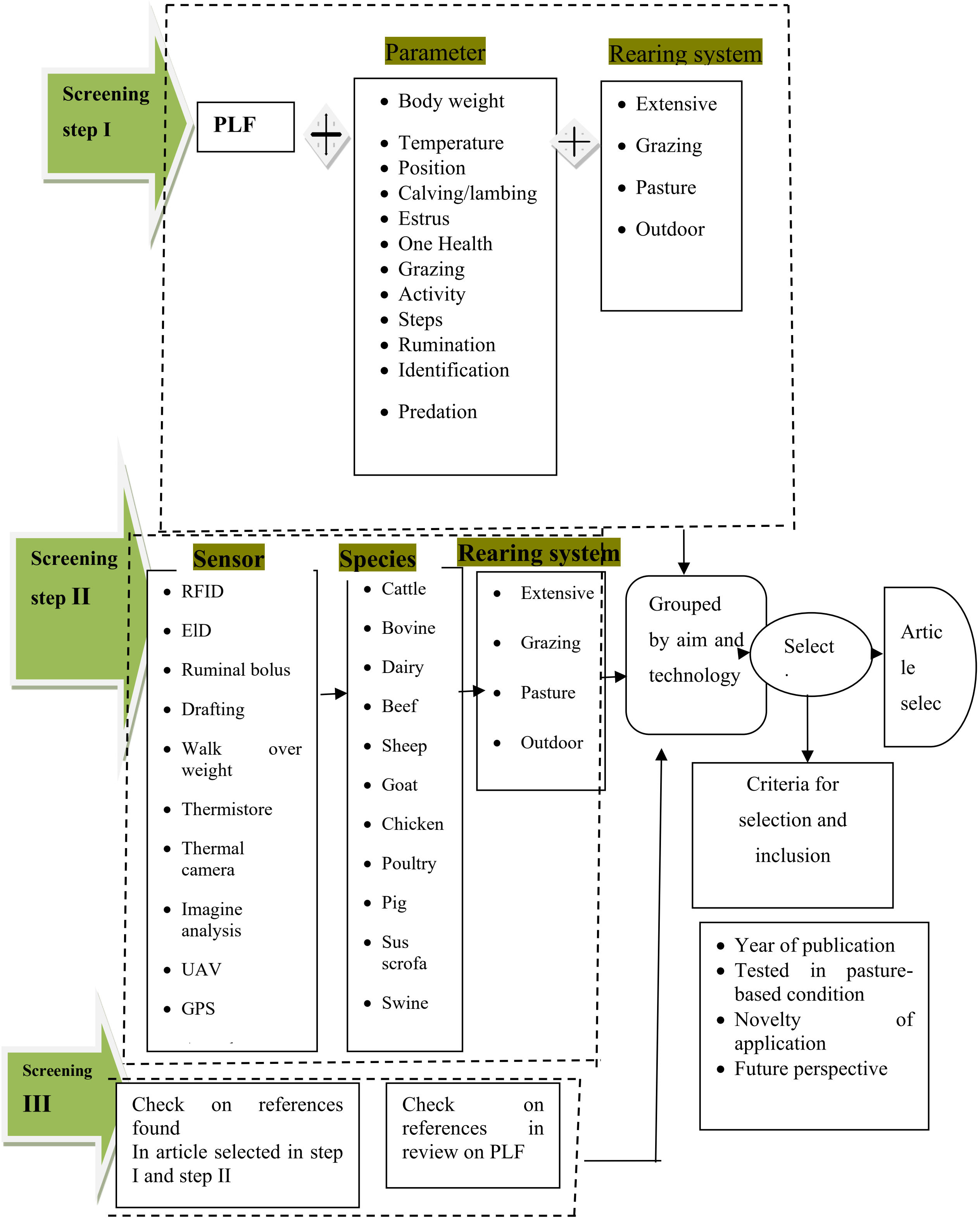
Figure 2: **Scheme of the Literature Searching Process Based on Keywords Related to the Parameter of Interest (e.g., BW, temperature, position, activity, one health, etc.), rearing system, sensor (e.g., accelerometer, global positioning systems, virtual fencing, etc.)**



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Research Quality Assessment

The evaluation and quality assessment were done to assess each study's quality and assist in removing the low-quality and irrelevant studies (Kitchenham, 2007). The evaluation was guided by five different criterion: (a) well-designed and practical experiments with enough datasets; (b) appropriate research methods and simulation platforms; (c) clear research objectives; (d) accurate and critical discussion and analysis; and (e) good significant to knowledge and technology advancement, (e) data of publication 2000 -2025;(f) geographic location – developing countries; (g) type of publication – peer reviewed journal, books, book chapters and working papers; (h) nature of research – systematic reviewes, narative reviews and meta-analysis reviews; (i) method used such as qualitative and quantitative; and (j) articles written in English language. Only those studies that satisfied two or more of the aforementioned criteria were taken into consideration for the literature. 155 papers were chosen as the referred publications based on the set quality evaluation criterion.

Three screening steps were considered, as shown in Figure 2. The first screening step explored parameters and rearing systems used in animal production using AI. The second screening identified articles that employ various sensors, species (cattle, dairy, beef, goat, sheep, pig, swine, chicken, poultry, bovine, etc.). This part also discusses the rearing systems used in animal productivity, such as pasture, grazing, extensive, and outdoor systems. The third screening step involved checking references found in articles selected in steps one and two, with an emphasis on the applications of PLF. These steps were combined and grouped, targeting the aim and technology used in the articles.

Data Extraction and Analysis

The review's research articles covered the years 2000 through 2025. For statistical analyses, the affiliation of the first author served as one of the parameters for data extraction. The information about the cited articles, such as their title, authors, publishing year, country, and list of journals published.

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Table 1: A Summary of Search Category, Identification, Screening, and Articles Included

Search Category	Identification		Screening		Included
		Duplicate removed (N = 25)	Records screened (N = 155)	Records excluded (N = 65)	
General literature	Records identified from databases (N =200)	Removed for other reasons (N = 20)	Reports sought for retrieval (N = 90)	Reports not retrieved (N = 35)	Studies included in review (N = 35)
			Reports assessed for eligibility (N = 55)	Reports excluded by the study criteria (N = 20)	
		Duplicate removed (N=2)	Records screened (N = 7)	Records excluded (N=4)	
Tanzanian case	Records identified from databases (N = 10)	Removed for other reasons (N = 1)	Reports sought for retrieval (N = 3)	Reports not retrieved (N = 0)	Studies included in review (N = 3)
			Reports assessed for eligibility (N = 3)	Reports excluded by the study criteria (N = 0)	

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FINDINGS AND RESULTS

Table 2: Reviewed Literature under PRISMA Guideline

Farm routine activities	Uses of AI technology	Challenges
Identification of animals	Wearable sensors used to identify animals	Lack of infrastructure
Disease diagnosis	Provide early disease diagnosis	Lack of technical expertise
Reproduction monitoring	It predicts the oestrus and calving time	High initial cost
Monitoring feeding	It is used in scheduling feeding.	Advanced monitoring tools (e.g., wearable devices or smart feeding systems) can be expensive. This can limit their accessibility in low-resource settings.
Milking	Use of an automated milking system	Inadequate equipment due to cost barriers
Hatchery monitoring	Used in monitoring hatchery conditions	Lack of automation and technology access barriers
One health surveillance platform	Used to provide timely, data-driven insights for disease prevention and control.	AI models trained on non-representative datasets can produce biased predictions.

We identified several roles of AI in livestock farming systems, animal monitoring, and husbandry, ranging from extensive to intensive livestock systems, but have also been applied in pasture-based systems.

Interdisciplinary Research

We conducted an interdisciplinary study to understand the technology and applications of AI in animal production. We address the issues of animal welfare, behaviour, disease, and environmental management for sustainable production. The technology has been the subject of research focus based on non-structured (such as image, video, and voice) and structured (such as textual) data collection, analysis, processing, recognition, and modelling that are related to animal behaviour, welfare, and diseases, as well as animal building designs and environmental management (Awan *et al.,* 2021b).

Animal Identification

AI can indeed be used for animal identification and has been employed in various fields such as wildlife conservation, veterinary medicine, and livestock management. AI –driven algorithms can be trained to recognise and classify animals based on their visual characteristics. AI can identify species, individuals, or specific features like patterns, markings, or colourations. This technology is particularly useful in wildlife research, where cameras or drones capture images for population monitoring and conservation efforts. AI algorithms can also be trained to identify animal species based on their vocalisations or sounds. This is especially relevant for birds, marine mammals, and certain terrestrial species that have distinct vocalisations. AI systems can process audio recordings to identify species, monitor migration patterns, and detect specific calls, while also recognising individual animals through analysis of distinctive physical traits or behavioural patterns.

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This can include analysing features like the shape of fins or flippers, unique markings or spots on animals, or even the texture of skin or fur. Such identification techniques are widely used in the study of marine animals like dolphins, whales, or sharks. RFID technology, combined with AI, enables individual identification and tracking of animals in livestock management systems. RFID tags can be attached to animals, and AI algorithms can process the collected data to monitor animal movements, behaviour, and health, and optimise farm management practices. AI can assist in DNA analysis for species identification and tracking genetic markers. Through the analysis of genetic data, AI algorithms can distinguish species or individuals, uncover genetic relationships, and support conservation initiatives as well as selective breeding programs.

Digital methods mainly consist of radio frequency identification tags (RFID) and can be grouped into boluses, ear tags, and injectable glass tags. The tag on the animal transmits the information by radiofrequency to the tag reader; usually, this is the only part of the system that requires an external power source. RFID offers an easy and affordable way to identify, track, and monitor livestock, thus improving the traceability of animals along the supply chain (Neethirajan *et al.,* 2017). The adoption of RFID technology in practical farm management has allowed the development of managerial software where daily records on individuals (e.g., medical treatments, growth performance, pedigree, reproductive performance, etc.) are automatically stored (Neethirajan *et al.,* 2017). The most widespread is the electronic ear tag, which is widely used in grazing systems and is a mandatory identification system in some countries, and also smart ear tags embedded with accelerometers (sensors) to detect several parameters related to animal welfare and reproductive performances are available on the market (e.g. Allflex SenseHub[1], SCR Engineers Ltd[2]). They can also be used to identify individuals, but their recognition as an official identification system depends on the countries. It's worth noting that the effectiveness of AI for animal identification depends on the quality and quantity of data available for training the algorithms. Accurate labelling of data is crucial for training AI models to achieve reliable results. Furthermore, AI systems must be continuously improved and refined to handle variations in environmental conditions, lighting, or other factors that may affect the accuracy of identification.

Body Weight

To simplify these animal routine practices, platforms known as ‘‘Walk-over-Weigh” (WOW) have been developed and applied in the dairy industry (Leroux *et al.,* 2023). However, they have become an option in pasture-based systems where animals remain for weeks or even months without being handled. Some improvements made in recent years, such as solar-powered batteries and data transmission systems, have allowed their use in rangelands for sheep and cattle. The WOW consists of a specially designed crate on which the animal walks, allowing the body mass to be estimated using continuous averaging techniques (Halachmi *et al.,* 2019). They can also be equipped with a tag reader to automatically identify the animal being weighed. The WOW is usually placed at a restricted entry point for an attractant (e.g., feed, water) so that when the animal enters, it is weighed and identified. Growth rates can then be calculated and used as prediction tools to monitor the condition of the animals, for example, for the early detection of pasture-borne nematode infections (Mushi *et al*., 2021), as well as to open new pasture areas when scarcity of resources starts affecting the growth. Automated data harvesting reduces stress on animals (with no handling necessary) and labour.

[1] https://www.allflexsa.com/products/monitoring/cow-monitoring/

[2] https://www.preqin.com/data/profile/asset/scr-engineers-ltd-/157676

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AI algorithms can analyse images or videos to estimate body weight based on visual cues. The algorithm can learn to identify patterns and features that correlate with weight by training the AI system on a dataset of images with corresponding body weight information. This technology can be useful for applications like monitoring livestock weight or estimating body weight in wildlife populations. AI can combine data from various sensors to estimate body weight accurately. For example, in livestock management, sensors such as load cells in feeding troughs or walk-over weighing platforms can collect weight-related data. Real-time body weight estimates can be obtained to facilitate precise feeding regimes and overall animal health monitoring by integrating this data with AI algorithms (George *et al.,* 2021). AI can be employed to develop predictive models that estimate body weight based on various input parameters. These models can utilise a combination of factors such as height, body measurements, age, gender, and other relevant variables to estimate body weight. An AI model, when trained on a large dataset of known weight measurements, can learn the relationships and patterns to make accurate predictions for individuals based on their characteristics.

Animal Location and Prevention of Livestock Theft

Targeting to help farmers identify locations of their animals, GPS devices have been used to prevent cattle theft and animal location tracking in several parts of the world. In an Italian study, where a GPS collar was coupled with the global system for mobile communication (GSM), animals were tracked using software that alerted the farmer when an animal moved outside its grazing area, denoted by a virtual perimeter (McKenzie *et al.,* 2021). Some alternatives to GPS for tracking the animals in pastures have been evaluated. The application of outdoor image analysis using top-view cameras, which are currently used indoors to monitor animals, was evaluated. In fenced pastures, Ruiz-Garcia & Lunadei (2011) applied a framework that combined low-cost time-lapse cameras, machine learning, and image registration to monitor the location of animals belonging to two flocks of goats. The obtained precision and sensitivity were 90% and 84.5%, respectively.

Animal Behaviour, Activity Time Budgets, and Grazing Intake

Animal behaviours (Brown et al., 2015) are always monitored by means of a camera (González-García et al., 2018), a microphone (Segerkvist et al., 2020), and an accelerometer (Tangorra et al., 2013). Accelerometers used to enhance animal welfare have been reported to detect lameness in grazing dairy (Bonneau et al., 2020) and beef (Zheng et al., 2018) cattle. They have also been used to record and classify standing, lying, resting, ruminating, and grazing behaviours in cattle and sheep (Nasirahmadi et al., 2019a; Aydin et al., 2015; Giovanetti et al., 2016). In addition to their low energy requirement, accelerometers are very accurate in detecting head position, which allows discrimination between grazing, lying, and standing (O'Leary et al., 2020). Different software systems (e.g., Python, Matlab, Tensorflow, etc.) and algorithms (e.g., CNN, ML, DL, etc.), which are used to translate or classify the visual or acoustic information from the acquired images and other data into certain behaviours, the feeding behaviour of animal individuals is an important indicator reflecting their healthy status. Water meters provide accurate water consumption information, which is considered a simple and effective way to monitor the drinking performance. AI algorithms can analyse video footage of animals to detect and classify different behaviours. By training the AI system on labelled video data, it can learn to recognise specific actions such as grazing, resting, walking, or social interactions. This enables researchers to study behaviour patterns, assess activity time budgets, and understand how animals allocate their time in different contexts.

It's important to note that the effectiveness of AI in analysing animal behaviour, estimating activity

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time budgets, and assessing grazing intake relies on the availability of accurate and diverse data for training the algorithms. Proper labelling and annotation of data are crucial to ensure the reliability of AI models. Additionally, the integration of AI with other monitoring techniques and domain expertise is often necessary to obtain comprehensive and accurate insights into animal behaviour and related parameters.

Herd Management

Animal herd management includes grazing, drinking, disease intervention and reproductions with artificial intelligence technology is made possible for famers to archive all of these with Systems consisting of GPS trackers and aerial pasture monitoring have been tested as supporting tools for grazing planning to avoid overgrazing and grassland degradation (Poulopoulou *et al.,* 2019) tri-axial magnetometer, temperature sensor which attached to animals as an ear tag can recognize standing, lying, resting, ruminating, and grazing behaviours in cattle and sheep (Nasirahmadi *et al.,* 2019a), (Aydin *et al.,* 2015), (Giovanetti *et al.,* 2016) this helps farmers to get early and real time data for easy decision making including early disease interventions.

Reproduction Monitoring: Oestrus, Parturition, Pedigree

Oestrus detection is always of economic importance in the productivity of animals, and the first sector to apply new computerised methods was dairy farms. Among the early automatic methods for oestrus detection, pedometers appear to be the most widespread (Yoshitoshi *et al.,* 2013). In recent years, accelerometers and integrated monitoring systems with embedded accelerometers have become popular for monitoring animal activity and predicting oestrus (Alvarenga *et al.,* 2016; Werner *et al.,* 2019). Accelerometers have also been used for calving detection.

Pasture Evaluation and Grazing Management

Assessing pasture availability and quality and quantity of pasture play a crucial role in the management of livestock, especially in cattle, goats, and sheep, and it's not easy with traditional methods as its evaluation is achieved through labour- and time-consuming methods (i.e., field measurements and chemical analysis). Acquiring data over a large range of time and space, remote sensing (RS) techniques represent a rapid and effective method for pasture monitoring. RS data are normally acquired through three different types of sources: optical sensors, synthetic aperture radar sensors, and light detection and ranging sensors (Heald *et al.,* 2000). The most commonly used optical sensors are based on space-borne sensors. These acquire multispectral images, at different spatial and temporal resolutions, to develop a grass production or a quality estimation regression model driven by field samples and vegetation indices, for example, the normalised difference vegetation index or biophysical variables (e.g., leaf area index), as highlighted in Pereira *et al.* (2018).

Health Monitoring and Detection

With the progress of AI technology, more studies were conducted on disease detection for sick animals like birds, cattle, pigs, sheep, and goats (Li *et al*., 2020; Abeni *et al.,* 2019). The sick bird could be identified by some symptoms of abnormal body temperature (Wachendorf *et al*., 2018) measured by a wearable wireless sensor (Wachendorf *et al.,* 2018), decreased feed intake and movement, and different sound patterns. Although the wearable sensing technology could achieve a good abnormal body temperature detection, it can only be used as early-stage warning because it cannot determine by which disease the livestock were infected and In the milk production, bacteriologic status of the mastitis in dairy herds could be analyzed and predicted using ANN and ANFIS models with complex data as the input variables to improve probabilities of diagnosing (Jin *et al.,* 2014).

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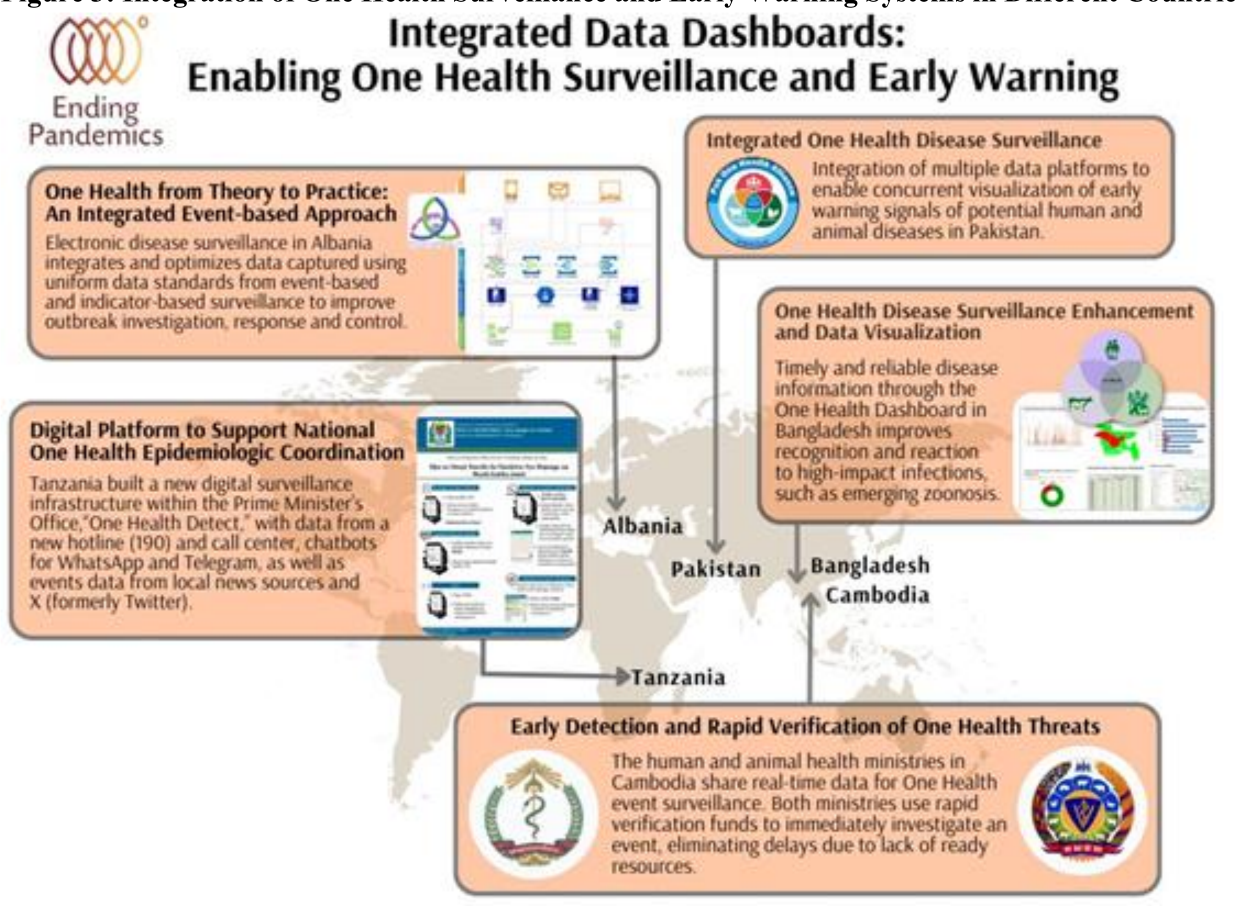
Digital One Health Surveillance Platform

One Health animal surveillance refers to integrated systems that monitor health events at the human-animal-environment interface. These systems are designed to detect zoonotic diseases, antimicrobial resistance, environmental threats, and other health risks early by combining data from multiple sources: veterinary clinics, livestock farmers, labs, wildlife, environmental sensors, and sometimes community and market observations. The surveillance aims to enable faster response, better coordination among sectors, and improved public and animal health outcomes. The Digital One Health framework proposed by Loosli *et al. (*2023) strengthens the animal health and production value chain by integrating data from farms, veterinary services, laboratories, the environment, and markets into a unified digital system, enabling real-time information sharing and improved coordination across sectors. The framework enhances traceability, accuracy, and early detection of animal diseases while improving monitoring of antimicrobial use.

Figure 3: Integration of One Health Surveillance and Early Warning Systems in Different Countries



DISCUSSION

The findings of this review indicate that AI-based smart livestock farming has the potential to improve animal health and production in Tanzania. AI has the potential to revolutionise animal farming in Africa by improving productivity, efficiency, and sustainability. Here are some future perspectives on how AI could impact animal farming in Tanzania and Africa, as explored in the findings of this study:

Precision Livestock Farming

AI-driven PLF integrates on-animal sensors, stationary cameras, drone imagery, and

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environmental sensors with machine-learning analytics to create continuous, individualised digital profiles of animals and herds. AI systems can detect deviations from normal behaviour or physiology, enable precision feeding and micro-management, and support welfare-centric decisions that increase productivity and reduce losses by fusing movement, vocalisation, rumination, temperature, weight, and image/video data in real time. PLF shifts farm management from periodic observation to continuous, data-informed care, especially valuable where early detection and fine-tuned management raise yields and animal wellbeing. Trabachini *et al.* (2025) present a systematic literature review of precision livestock farming (PLF) in swine. They classify technologies into thematic groups, apply a SWOT analysis, and report that 37% of the studies focused on animal identification and monitoring, while 28% addressed welfare issues. The review highlights major opportunities for PLF to optimise production, enhance welfare, and reduce environmental impact, but also emphasises significant barriers: a lack of standardised metrics and limited investment in AI systems tailored to animal-welfare contexts. Michelena *et al.* (2024) provide a review of PLF in dairy and beef cattle, covering sensors/hardware, datasets, event detection (diseases, behaviours), and intelligent techniques. They note that while PLF adoption is increasing, the literature remains heterogeneous and fragmented in methods and metrics, indicating strong research needs for data standardisation and interoperability.

Disease Detection and Management

AI models such as supervised classifiers, deep-learning image analysis, and hybrid statistical–ML systems) are trained on multimodal inputs, clinical signs, farm sensor streams, genomic markers, and environmental variables, to perform syndromic surveillance, outbreak prediction, and case prioritisation. These tools strengthen early warning, targeted vaccination, and biosecurity measures, reducing transmission and economic losses. In low-resource settings, AI can be integrated with mobile reporting to amplify veterinary reach and optimise scarce intervention resources (Nchimbi et al., 2022). Heinen *et al.* (2025) provide a review on predictive modelling of cattle diseases, covering various outcomes (respiratory disease, bovine TB, lumpy skin disease) and algorithm types (neural networks, linear models). They find wide variation in accuracy, emphasise the need for balanced data sets (rare disease outcomes present challenges), and recommend multi-metric evaluation of AI models. Menezes (2024) offers a narrative review on AI for livestock, including computer vision systems and large language models. He reports on applications in behaviour monitoring, body-weight estimation, disease detection, and highlights emerging LLM usage for knowledge retrieval in animal farming contexts.

Automated Farming Operations

Autonomous devices and robotics, autonomous feeders, milking robots, robotic scrapers, and UAVs for inspection, combined with AI planners and perception modules, automate repetitive husbandry tasks and standardise care. Automation reduces dependence on manual labour, improves consistency (e.g., milking frequency, feed delivery), and frees staff for higher-value tasks such as animal welfare oversight and data-driven decision-making. When coupled with predictive maintenance and energy optimisation, robotic systems also increase uptime and lower operational costs. The recent paper focused on a very specific recent peer-reviewed review exclusively on automated feeding/milking robots in livestock, which was not located in the five publishers requested; the following provides context.) Padhiary, M., *et al.* (2024) review machine-learning and AI vision applications in farm automation, covering semi-autonomous systems, robotics, and cameras for tasks relevant to livestock automation.

Genetic Selection and Breeding

AI can assist in the genetic selection and breeding of animals by analysing vast amounts of genetic data. By identifying desirable traits and predicting the genetic potential of animals, AI can help farmers breed livestock with improved productivity, disease resistance, and adaptability to local conditions. A recent study in Genetics Selection Evolution (2025) on feed intake and body-weight gain using genomic and rumen metagenomics data demonstrates how prediction accuracy improves with AI models combining multi-omics and sensor data.

Environmental Sustainability

AI can optimise resource management in animal farming, leading to reduced environmental impacts. AI systems can optimise feed conversion, reduce emissions, and minimise resource wastage by analysing data on feed composition, energy consumption, and waste management. Tullo *et al.* (2019) examine precision livestock farming as a mitigation strategy for environmental impact in the *Science of the Total Environment*. They show how sensor data and PLF can reduce resource use and emissions and improve sustainability.

Market Forecasting and Supply Chain Management:

AI can help farmers make informed decisions by providing market forecasts, demand predictions, and price trends. By analysing data from various sources such as weather patterns, market trends, and consumer preferences, AI can support farmers in optimising production, managing supply chains, and enhancing profitability. Elufioye *et al.* (2024) review AI-driven predictive analytics in agricultural supply chains. They find that AI improves demand forecasting and supply-chain optimisation, but highlight infrastructure, data quality, and skills as substantial barriers.

Knowledge and Information Access

AI-powered chatbots and mobile applications can provide farmers with instant access to information and expert advice. These tools can assist in diagnosing livestock health issues, providing recommendations, and disseminating best practices, even in remote areas with limited access to veterinary services. While fewer large-scale reviews focus solely on chatbots/mobile apps for livestock, Menezes (2024) discusses LLM and knowledge-retrieval applications in livestock. Also, a PLF in swine (Trabachini *et al.,* 2025) comments on the need for improved human-machine interfaces and farmer-oriented decision tools. The research indicates a transition from sensor data to farmer actionable knowledge via digital platforms.

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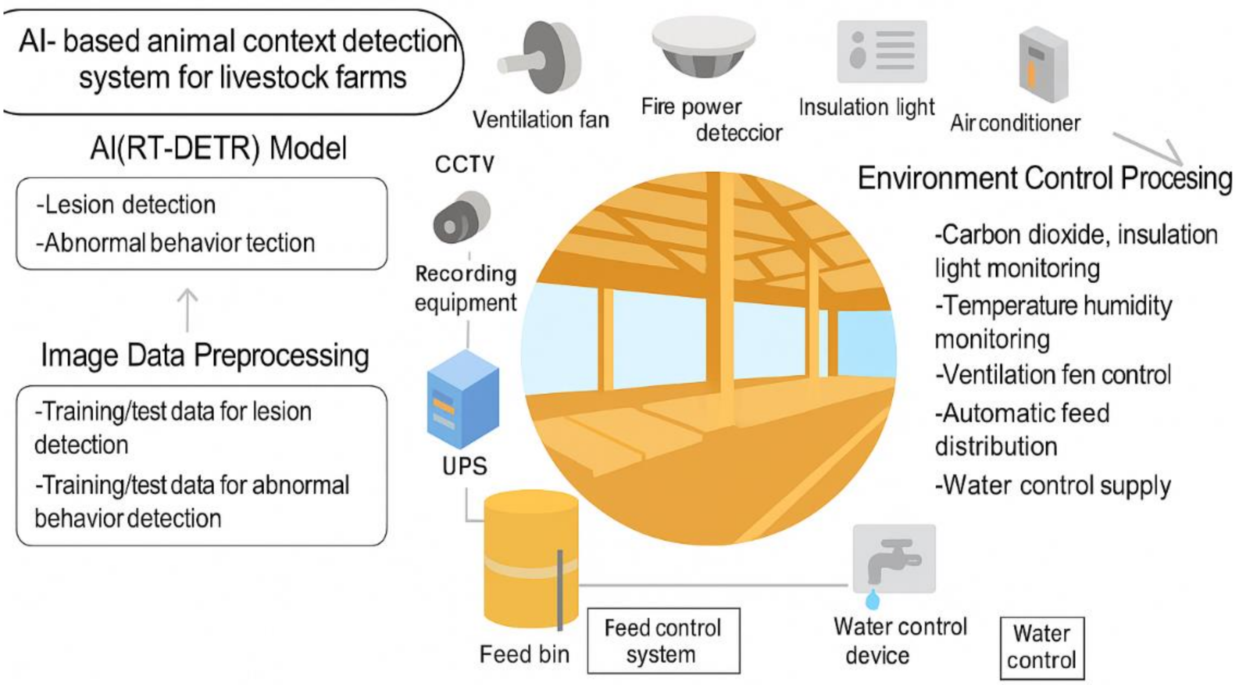
Figure 4: A Framework for the AI-Based Smart Monitoring of Livestock Farms

AI-based Smart Monitoring of Livestock Farms



Shin *et al*. (2023) propose an AI-based animal context detection system for smart livestock farms (see Fig. 3), integrating AI, IoT sensors, and automation technologies to enhance animal welfare, health monitoring, and farm efficiency. At the centre of the system are the livestock animals (e.g., Hanwoo cattle) housed within a barn equipped with multiple interconnected smart devices and sensors. Surrounding them is an AI-enabled monitoring framework that combines real-time environmental sensing with behavioural and health detection through video analytics.

AI (RT-DETR) Model and Image Processing

On the left side of the diagram, the AI (RT-DETR) model operates through data collected from CCTV cameras installed in the barn with the following functionalities:

Image Data Preprocessing involves preparing training and testing datasets for lesion detection (e.g., wounds, dirt patches, or infections on the cattle's body) and abnormal behaviour detection (e.g., excessive lying down, limping, or isolation).

The AI model analyses the live CCTV footage to detect signs of disease or distress using deep learning-based object recognition techniques.

Once an abnormality is detected, such as a cow remaining motionless for more than an hour or showing physical lesions, the system alerts farm managers for immediate intervention. This approach reduces the need for constant human surveillance, enabling continuous, automated, and accurate livestock monitoring using existing camera infrastructure.

Environmental Control Processing

On the right side of the diagram, the Environment Control Processing unit integrates data from multiple sensors:

- Temperature and humidity sensors, CO_2 sensors, and insulation light monitors continuously track barn conditions.

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- Ventilation fans, air conditioners, and water control systems automatically adjust environmental parameters to maintain optimal comfort levels for the animals.
- Feed bins and water devices are connected to automatic control systems that regulate feed distribution and water supply.
- This closed-loop control system ensures that animals live in a stable, clean, and thermally comfortable environment, which is vital for their welfare and productivity.

Integration and Smart Farm Management

- All systems, AI monitoring, CCTV data, environmental sensors, and control devices—are integrated into a centralised management network.
- The data collected supports evidence-based decision-making, enabling farm managers to respond proactively to changes in animal health or environmental conditions.
- Through automation and AI-driven analytics, the system reduces labour costs, minimises health risks, and enhances the overall sustainability and intelligence of livestock operations.

Implementation Gaps, Opportunities, and Future Research Directions

Implementation Gaps in AI-Based Smart Livestock Farming

Despite the growing global adoption of AI in livestock systems, several interrelated gaps continue to limit its effective implementation in Tanzania and comparable low- and middle-income contexts.

Digital Infrastructure and Connectivity Gaps

Limited broadband coverage, unreliable mobile networks, and inconsistent electricity supply, particularly in rural and pastoral areas, constrain the deployment of AI-enabled sensing systems, cloud-based analytics, and real-time monitoring tools. These infrastructural limitations hinder continuous data acquisition, model updating, and timely disease surveillance essential for One Health outcomes. Paget *et al.* (2025) examine how inclusive digital development can be achieved in w-resource contexts through a frugal innovation strategy, drawing empirical evidence from three smallholder agriculture value chains in West Africa. The authors argue that conventional digitalisation approaches often fail to reach smallholder farmers due to high costs, limited infrastructure, low digital literacy, and weak institutional coordination. The paper demonstrates that frugal digital solutions, characterised by affordability, simplicity, adaptability, and strong local embedding, are more effective in promoting inclusion and value creation. The findings highlight the importance of aligning digital tools with existing socio-economic practices, strengthening intermediary actors (e.g., cooperatives and extension services), and fostering co-design with end users.

High Cost of AI Technologies and Limited Affordability

AI-driven solutions such as smart sensors, automated feeding systems, wearable devices, and machine vision platforms remain costly for smallholder and medium-scale livestock farmers (Miller *et al*., 2025). The absence of affordable financing models, subsidies, or localised low-cost innovations restricts scalability and long-term sustainability.

Data Scarcity and Lack of Standardisation

The effectiveness of AI systems depends heavily on high-quality, labelled, and interoperable datasets. However, livestock data in Africa are fragmented, inconsistent, and often collected manually. The lack of standardised national datasets on animal health, genetics, production metrics, and environmental conditions limits the development of robust predictive and transferable AI models.

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Limited Human Capacity and Digital Literacy

Low levels of AI awareness and digital skills among farmers, extension officers, and veterinary practitioners hinder adoption and trust in AI-based recommendations. This gap affects system usability, maintenance, and interpretation of AI outputs, reducing the practical impact of deployed technologies. Aranguri *et al.* (2025) examine how digital literacy influences the adoption of digital technologies in the agricultural sector. The authors analyse existing empirical and conceptual studies to identify key factors that enable or hinder farmers' adoption of digital tools, such as precision agriculture technologies, mobile applications, decision-support systems, and data-driven farming solutions. The authors further find that digital literacy is a critical enabler of technology adoption, closely linked to farmers' education levels, access to training, age, and prior exposure to ICTs.

Weak Institutional and Policy Alignment

Fragmented coordination among agricultural, veterinary, ICT, and environmental institutions results in limited integration of AI solutions within national livestock, One Health, and digital agriculture strategies. The absence of clear regulatory frameworks for data governance, AI ethics, and interoperability further constrains implementation.

Opportunities for Advancing AI-Based Smart Livestock Systems

Despite these challenges, African countries present significant opportunities to leverage AI for transforming livestock systems and improving Animal One Health and productivity.

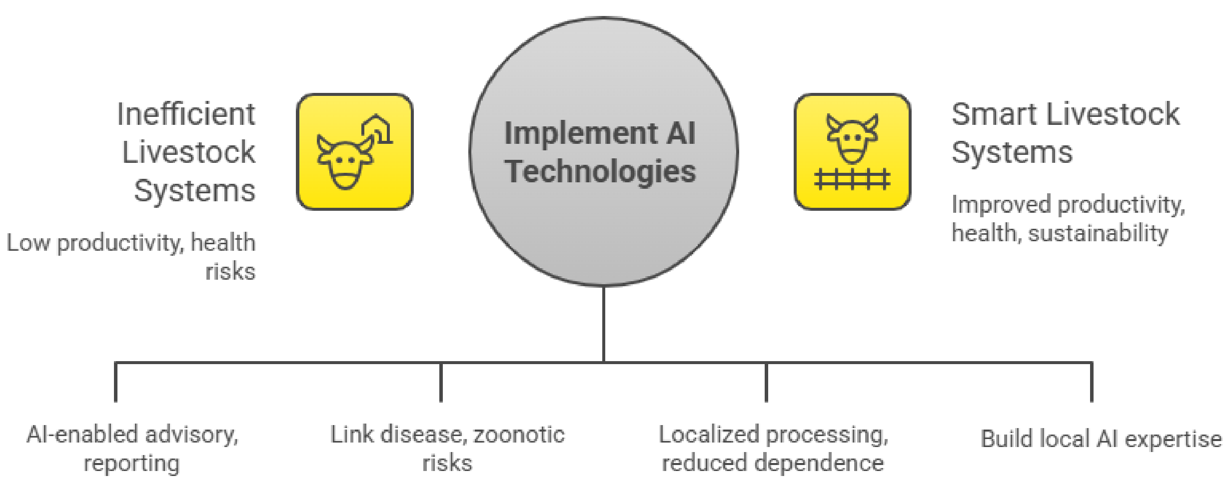
Expanding Mobile Penetration and Digital Agriculture Initiatives

The increasing adoption of mobile phones and digital platforms in African countries provides a foundation for AI-enabled livestock advisory services, mobile-based disease reporting, and remote farm management systems tailored to smallholders.

Integration of One Health and AI Frameworks

AI offers a powerful tool to operationalise the One Health approach by integrating animal health, human health, and environmental data. Early warning systems linking livestock disease outbreaks with zoonotic risks and environmental drivers can significantly enhance national preparedness and response capabilities.

Figure 5: Opportunities for Advancing AI in Based Smart Livestock Systems



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Emerging Low-Cost Sensors and Edge AI Technologies

Advances in low-power IoT devices, edge computing, and open-source AI frameworks enable localised processing, reduced connectivity dependence, and cost-effective deployment in remote livestock systems.

Youth Engagement and Capacity Development

The growing pool of digitally skilled youth and data scientists presents an opportunity to build local expertise in AI-driven livestock innovation, fostering sustainability and reducing reliance on external technologies.

Future Research Directions

To fully realise the potential of AI-based smart livestock farming, future research should focus on the following priority areas. Figure 6 indicates the future research directions in AI-driven livestock farming.

Predictive Disease Modelling and Early Warning Systems

Future studies should develop AI models that integrate multisource data, clinical records, sensor data, climate variables, and mobility patterns to predict disease outbreaks and antimicrobial resistance trends. Emphasis should be placed on explainable blockchain –based AI models that support veterinary decision-making and policy interventions under the One Health framework.

Automated and Precision Farm Operations

Research is needed on AI-driven automation for feeding, milking, health monitoring, and waste management. Computer vision, robotics, and reinforcement learning can optimise farm operations, reduce labour intensity, and improve animal welfare, particularly in intensive and semi-intensive production systems.

AI-Assisted Genetic Selection and Breeding Programs

Future work should explore machine learning approaches for genetic evaluation, breeding value prediction, and phenotype–genotype association analysis. Integrating AI with genomics can support climate-resilient, disease-resistant, and high-yield livestock breeds adapted to local environments.

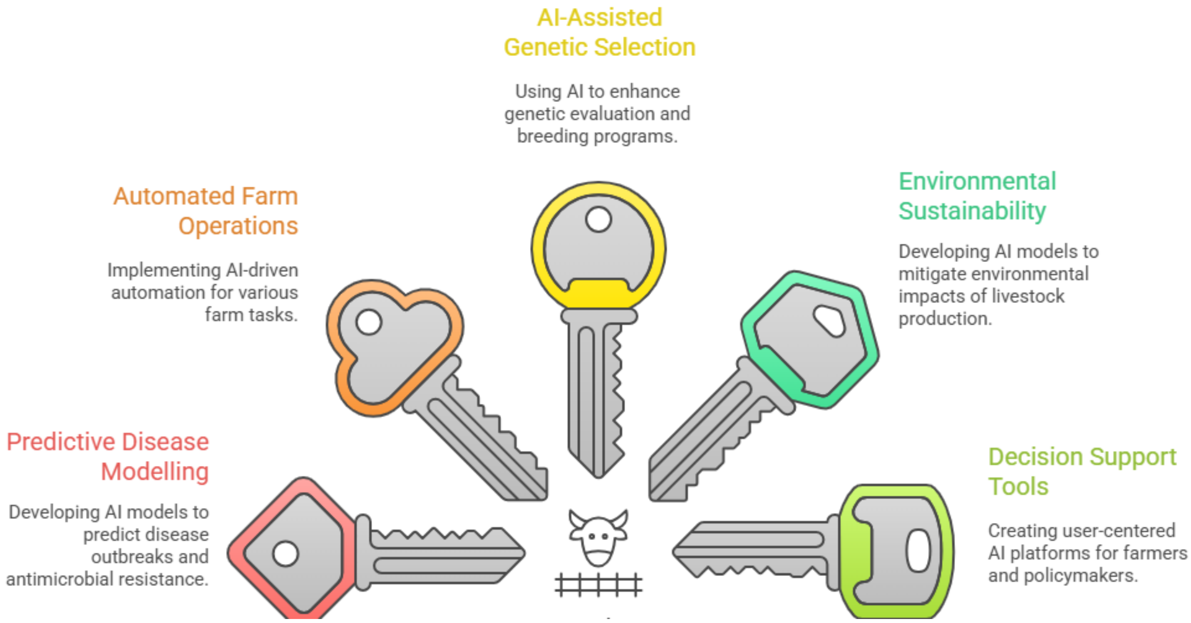
Environmental Sustainability and Climate Resilience

AI-based models should be developed to assess and mitigate the environmental impacts of livestock production, including greenhouse gas emissions, land degradation, and water use. Integrating remote sensing, climate data, and livestock performance metrics can support sustainable and climate-smart livestock systems.

AI-Supported Decision Support Tools for Farmers and Policymakers

There is a need for user-centred AI decision-support platforms that translate complex analytics into actionable insights for farmers, extension officers, and policymakers. Research should focus on usability, localization, language adaptation, and integration with national extension and veterinary information systems.

Figure 6: Future Research Directions in AI- Livestock Farming



It is important to note that the successful implementation of AI in animal farming in Africa would require overcoming challenges such as limited access to technology, infrastructure, and internet connectivity, as well as ensuring affordability and inclusivity for small-scale farmers. Government support, investment in research and development, and partnerships between technology providers, agricultural organisations, and local communities will be crucial in realising the full potential of AI in animal farming in Africa. Therefore, there is a need for further research and investment in this area to fully realise the potential of AI-based smart farming in Tanzania. Furthermore, it is essential to provide technical support and training to farmers to ensure they have the necessary skills to use the technology effectively.

CONCLUSION AND RECOMMENDATION

AI-based smart farming has the potential to revolutionise livestock farming in Tanzania by improving animal health and production. However, to fully realise its potential, there is a need for increased investment in technology and infrastructure, as well as awareness and training among farmers. However, its successful implementation requires addressing the farmers' challenges identified in the studies. Therefore, we recommend that the government invest in infrastructure and provide technical support to farmers to facilitate the adoption of AI-based smart livestock farming. Additionally, stakeholders in the livestock sector should collaborate to create awareness and educate farmers on the benefits of these technologies.

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