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A systematic literature review on deep learning and IoT for livestock management, monitoring, and anti-theft applications

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ABSTRACT

In recent years, the integration of Deep Learning (DL) and the Internet of Things (IoT) has brought new possibilities to livestock management, offering smart ways to monitor animal health, behavior, and security. Yet, several challenges remain. These include the high cost of deploying advanced sensors in rural areas, inconsistencies in data collected from different environments, and the limited ability of models to adapt to varying farm conditions. There's also a lack of standard datasets and difficulty in achieving real-time, reliable results at scale. In this paper, we present a detailed review of the current state of DL and IoT technologies in livestock systems. Using the PRISMA framework, we reviewed 50 studies from reputable sources such as Scopus, IEEE Xplore, and Web of Science. Our analysis covers key use cases—including animal identification, tracking, health monitoring, and theft prevention—and highlights the deep learning models most commonly used, such as CNNs, RNNs, LSTMs, and SVMs. This study contributes by offering: (1) a clear picture of how DL and IoT are being applied in real-world livestock settings, (2) a categorization of models and methods by application area, and (3) insights into ongoing technical and deployment challenges. Looking ahead, future work should explore the creation of open and diverse datasets, the development of lightweight AI models suitable for farm-based edge devices, and privacy-aware solutions that ensure both data security and scalability for smart agriculture.

Keywords: Deep Learning, Management and Monitoring, Livestock, Internet of Things, Farm.

1. INTRODUCTION

The fourth Industrial Revolution (Industry 4.0) is transforming various industries, including agriculture, through technologies such as Artificial Intelligence (AI) and the Internet of Things (IoT). Different technologies have been used in livestock management to track and locate animals in real time. However, in these advanced mechanisms, there is a lack of comprehensive research evaluating how deep learning models, such as CNN, RNN, and YOLO, contribute to livestock monitoring, disease detection, and anti-theft mechanisms. This study addresses this gap by conducting a systematic review of the existing literature, highlighting key trends, challenges, and opportunities in AI-driven livestock management.

With this rapid progress, it is essential to take a step back and assess how deep learning is being applied in livestock management, particularly in monitoring and anti-theft solutions. A systematic review of these applications is both timely and necessary to understand the full potential of AI in this field.

A. Livestock

The livestock sector is expanding quickly, ensuring food security for approximately 1.3 billion people and accounting for 40% of global agricultural production [1].

Effective livestock management and monitoring are crucial in agriculture for several reasons, including managing disease outbreaks, ensuring dairy production, administering regular vaccinations, and meeting meat consumption needs especially as The world's population is projected to grow to 9.2 billion by the year 2050 [2]. Management the livestock is an essential task of farm management, so the traditional Manually counting animals across vast farmland spanning.



Fig. 1. Applications of AI and IoT in Livestock Management and Monitoring

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hundreds of acres is a tedious process and susceptible to human errors, making it an inefficient task. The industry faces numerous challenges related to traditional farming, where everything is done manually. Farmers have to manage and monitor livestock, which is time-consuming and physically demanding, potentially leading to negative outcomes. For instance, when a farmer is counting cattle, the numbers can lead to double-counting the same animals. If an animal is sick or missing, it may be difficult for the farmer to quickly identify the issue and call for emergency assistance, among other challenges. In Brazil, cattle are typically counted manually by guiding them through a corral, a labor-intensive process aimed at reducing errors. However, as the cattle population grows in more confined spaces, the likelihood of inaccuracies continues to rise [3]. Livestock theft leads to significant economic losses and negatively impacts animal welfare. Conventional livestock management and monitoring methods face challenges related to accuracy, efficiency, and real-time responsiveness.

Over the years, various methods have been used for identifying animals. Traditional techniques, such as tattooing and branding, involve applying ink or heat to the animal's skin, leaving permanent marks. However, these methods can cause discomfort and are vulnerable to alterations or counterfeiting. An alternative is microchipping, where a small chip with a unique serial number is inserted into the animal's nuchal ligament for identification. While studies suggest that microchip implantation is generally safe and effective, it's important to recognize that, like any medical procedure, there may be potential risks and limitations [4]. However, many identification methods are susceptible to loss or damage caused by animal movement, physical interactions, or bites. Moreover, electronic devices are at risk of being tampered with, hacked, or exchanged between animals, potentially leading to fraud. Moreover, the costs of these systems can become significant, especially when managing large herds [5]. There are growing concerns about challenges such as livestock tracking, automated cattle health monitoring, farm security risks, and the slow advancements in crop production [6].

One drawback of microchipping animals is the expense of both the chip and the implantation process, which can be a financial burden for some farmers. Additionally, reading microchips requires specialized scanners, which may not always be accessible. This can make it difficult to identify a lost animal if the person who finds it doesn't have a scanner on hand. Plus, not all scanners can read every type of chip, so there is a chance that even if an animal is chipped, they might not be recognized right away. And while the chips are designed to be small and safe, their size can sometimes make them harder to read [4].

A. IoT in the smart Farming

IoT-powered smart farming facilitates data-driven decisions, precision agriculture, and sustainable practices. In modern livestock farming, IoT technologies have become essential for enhancing efficiency and management. Researchers have harnessed these innovations to revolutionize livestock environments, ensuring optimal conditions for animal health and productivity.

1) safety Monitoring and Assistance : Safety monitoring and assistance entail examining data and metrics related to identifying environmental hazards. These hazards could potentially endanger the surroundings and lead to adverse consequences on the farm.

We are currently in a digital world where everything is based on the technology to improve the productivity, monitoring, health checking, blood pressure, pregnancy of the livestock and job creation. In the past farming sector depended on the farmers skills, experience, talent, and the environment aspect as well. However nowadays smart farms do not relying on the farming experience and environment aspect. In this study, our focus is on livestock counting, classification using IoT and computer vision. Sensors and devices can establish internet connectivity through multiple channels, including cellular networks, satellite, Wi-Fi, Bluetooth, LPWAN (Low-Power Wide-Area Network), or direct Ethernet connections. Incorporating IoT into smart farming paves the way for precision agriculture, enhancing both crop quality and livestock health. With the help of smart farming sensors and wearable technology, farmers can access real-time updates at their fingertips. IoT-enabled smart farming systems allow for monitoring and tracking the entire farm, including the management of human resources, tools, and institutional assets. Real-time health monitoring of livestock can also significantly reduce costs, boosting profits for farmers [7]. IoT enables the optimization of processes that once required significant resources. The agricultural industry has already benefited from IoT-driven innovations, addressing challenges such as precision farming, greenhouse management, and livestock monitoring." This revision keeps the original message but makes it more unique. Let me know if you need further adjustments [8].

Monitoring livestock is crucial for observing cattle behavior and ensuring effective farm management on a personalized basis. The objective is to monitor cattle over extended periods, enabling in-depth analysis of their behavior; Wearable devices such as ear tags and collars with Radio Frequency Identification (RFID) technology are commonly used for this purpose. Other tools like accelerometers and Global Positioning System (GPS) devices help calculate grazing time, with sensors being widely utilized for cattle tracking. RFID-based sensors are particularly popular due to their standardized specifications and ability to provide identity information for each animal. However, this method has limitations, including challenges related to the placement of tag readers and the impact of environmental factors [9]. WSNs helps to control measure body temperature, behavior, health condition and movement of the livestock. RFID electronic ear tags are commonly used on large-scale farms to identify individual pigs. However, issues such as variations in ear tag quality, damage from farm equipment, and biting between pigs can cause the tags to fall off easily. This results in the loss or misplacement of important production and genetic breeding data, which can negatively impact smart farming management. Therefore, accurately detecting ear tag loss in real time is crucial for effective breeding management and genetic improvement in pig production [10]. Objects equipped with an RFID microchip are assigned a 'tag' and are automatically recognized by radio frequency when brought near a device known as an interrogator. LoRa is a low-power radio communication protocol designed for transmitting small amounts of data over distances ranging from 2 to 5 kilometers in urban environments, and up to 45 kilometers in rural areas. Similar to Sigfox, it is ideal for low-energy devices that send data intermittently, such as sensors. The Internet of Things (IoT) and Artificial Intelligence (AI) has had a significant positive impact on livestock management and monitoring, a concept known as Precision Livestock Farming (PLF). Since its rise in the late 1990s, IoT has played a pivotal role in livestock management (LsM).

Researchers such as Akhigbe, Munir, Akinade, Akanbi, and Oyedele, as well as Iwasaki, Morita, and Nagata, emphasize that IoT has gained considerable attention and is becoming increasingly important in LSM. They highlight that data is central to this progress, as informed decisions are essential in any field. Without solid data, decisions are often based on intuition rather than facts. While traditional practices in LSM remain in use, there is a growing need for a more data-driven approach. The researchers agree that collecting vast amounts of data enhances efficiency. To achieve this, monitoring technologies and their data collection tools offer an effective solution [11]. Conventional methods of animal identification can be broadly categorized into mechanical or electronic techniques, such as tattoos, branding, and RFID tags, as well as traditional biometric methods, including DNA analysis, iris patterns, and muzzle prints [12]. However these methods are time consuming, human efforts and the animals are always infected and painful.

The deployment of these technologies is limited by factors such as high energy consumption, large physical size, cost, and the availability of local communication networks, especially in expansive or remote areas [1].

Radio Frequency Identification (RFID) While this approach is effective in certain situations and has become a standard practice for livestock management in many countries, it also faces limitations. The data collection process can be time-consuming, and maintaining the sensor devices requires significant effort. These challenges make the system costly, inefficient, and often impractical for managing large populations of animals [12]. To address these challenges, recent studies have introduced automated systems using RGB cameras to monitor cattle behavior with minimal human intervention [9].

The Association for UAV Systems International projects that the UAV industry will generate over 100,000 new job opportunities by 2025. By 2027, the global market for UAVs is expected to be worth \$3 billion, with North America, Asia, and Europe leading the market. [4].

UAVs ability to access distant locations efficiently, without the need for human presence. Additionally, UAVs (Unmanned Aerial Vehicles) offer high mobility, low maintenance requirements, and easy deployment, which has simplified outdoor aerial image collection and streamlined monitoring and analysis processes. One of the most promising applications for UAVs is in agriculture, where they provide farmers with an aerial view of their entire fields. This technology can enhance efficiency by allowing farmers to easily analyze the land, eliminating the need for time-consuming manual inspections. Livestock farming, as a key component of agriculture, also benefits from this technology. Drones can play a crucial role in monitoring, tracking, and detecting animals, locating grazing areas, and alerting farmers to any unusual conditions that may pose a threat to the herd [13].

UAV has brought a particular output in the farmer sectors for the animal monitoring and management of the livestock in hug environment where it was a challenge to reach the ground to reduce the human efforts error and time consuming. UAV can fly to capture high resolution images and videos to control the animals in extensive to monitor the behavior of the livestock in real time. Unmanned aerial vehicles (UAVs) are seeing significant growth, particularly for monitoring purposes, offering advantages over traditional aircraft due to their flexibility, compact size, and cost-effectiveness. The suggested UAV-based monitoring system is designed for agricultural applications, including tracking livestock on farms.

The drone can fly over pastures to scan the animals, providing valuable data not only for farmers but also for relevant authorities responsible for animal subsidies [7]. More studies have focused on detecting and quantifying animals using drone imagery. In the past, conventional methods relied on recording video footage of the specific area for subsequent manual analysis.

2) Artificial intelligent and Deep learning Techniques Live-stock management and monitoring : Deep learning gained popularity around 2006 due to significant advances in computing power and the availability of labeled training data. During this time, researchers made substantial improvements to the architecture of neural networks. Deep convolutional neural networks have brought about a significant transformation in image classification [14], [15], [16], [17].

The advancement of AI has revolutionized livestock man.

TABLE I: COMPARISON OF RELATED STUDIES BASED ON COMMON CHARACTERISTICS IOT AND AI, ML, DL, CV.

Ref. Smart farms Technology year age ment and oversight, addressing challenges such as trace- ability, health monitoring, production, distribution, and con- sumption. It enhances efficiency, reduces waste, and improves video surveillance cameras in wildlife DL, IoT 2019 product quality. The use of deep learning, alongside other ma-Smart farming DL, IoT 2020chine learning techniques, has surpassed traditional methods in image processing and classification. The data collection, analysis and real-time decision-making process are entertained with the use of artificial intelligence (AI), machine learning (ML), and deep learning (DL) tools in this field [13]. AI is primarily applied in smart farming for tasks such as crop monitoring.

- Smart farming System
- Animal Activity Recognition
- Animal health conditions Monitoring

welfare of poul- IoT, NN 2021

IoT, TL, DL 2022

ML, IoT 2022

CV, IoT 2023predicting yields, detecting diseases, and optimizing resource management through improved decision-making and insights. AI and DL plays a crucial role in smart farms, encompassing Our review try Smart farming IoT and DL 2019-2024 animals monitoring in real time, yield prediction, disease de- tection, wearable devices management , supply chain planning, quality assurance, and demand analysis. The muzzle pattern of a cow is unique and can be used for identification purposes. Researchers have developed computer vision algorithms that can analyze muzzle images to distinguish between individual cows This can include features like the eyes, ears, and the shape of the head. More techniques can approaches to solve the challenges in the smart farm. Artificial intelligence has the potential to significantly improve all aspects of animal farming practices by providing innovative solutions for monitoring, management, and decision-making.

reviewed by several authors [18], [19]. This paper is struc- tured as follows: Section 2 presents a review of related work, followed by a summary and discussion of the findings in Section 3. Section 4 offers the concluding remarks.

In contrast to previous reviews that concentrated on live- stock management, security, and activity recognition, our analysis is not limited to specific application domains. Instead, we aim to provide a comprehensive overview of all areas and the diverse range of livestock management and monitoring technologies.

Deep learning (CNN, RCNN, SVM, YOLO V8) and internet of Things capture our attention for deep analysis of the development in this area. (see Table 2).

3) Application of deep learning in livestock management:

Deep learning, a branch of artificial intelligence (AI), focuses on training neural networks using extensive datasets to identify patterns and make informed decisions.

Recent developments in artificial intelligence (AI) and computer vision have facilitated the integration of deep learning models into the livestock industry. The application of deep learning in poultry health and welfare management is growing, with techniques such as Faster R-CNN, You Only Look Once (YOLO), and Single Shot Multibox Detector (SSD) being increasingly used for object detection in poultry in recent years. [26].

Deep learning (DL) is favored over other shallow learning and machine learning techniques due to its ability to use multi-layered neural networks that autonomously learn representations from raw data. This enables DL to identify intricate patterns and features. It excels at handling large, high-dimensional datasets, making it particularly effective for complex tasks like image classification, object detection, and spatiotemporal analysis. While DL has a wide range of applications, there is still limited understanding of how different DL models can be applied to specific problems. As a result, the challenges in designing, developing, and deploying these models have yet to be fully addressed [27]. The artificial intelligence algorithms often used in livestock monitoring are: CNN, RNN, LSTM, GANs, DRL, YOLO, RCNN, etc.

Convolutional Neural Networks (CNNs) are commonly employed for image recognition tasks, such as identifying individual cows or detecting health problems through visual indicators, like lumpy skin disease (LSD) and foot-and-mouth disease (FMD) [28].

Recurrent Neural Networks (RNNs): RNNs are helpful in analysing time-series data, such as milk production patterns or feeding behaviour. They can help predict future trends or identify anomalies [28].

Long Short Term Memory (LSTM) Networks: It is a type of RNN that particularly affects the collection of long-term dependencies in sequential data. They have been used to analyze data from sensors attached to cows, such as activity monitors or rumination sensors [28].

Generative Adversarial Networks (GANs): GANs can generate synthetic data that closely resembles actual data. These can be useful for augmenting small datasets or creating simulated environments for testing and training purposes [28].

Deep Reinforcement Learning (DRL): DRL algorithms can optimise decision-making processes on a dairy farm. For example, they can learn to control automated feeding systems or develop strategies for managing herd health [28].

In livestock management, deep learning can be applied in various ways:

- **Animal Identification and Tracking:** Deep learning models can accurately identify and track individual animals using computer vision techniques. For instance, facial recognition systems for cows have been developed to ensure accurate traceability and welfare assessment. These systems use a combination of face detection, cropping, encoding, and lookup to identify animals with high accuracy.

- **Health Monitoring:** Deep learning algorithms can analyze video footage and sensor data to monitor the health and behavior of livestock. By detecting anomalies in movement, posture, or feeding patterns, these systems can alert farmers to potential health issues early on. This proactive approach helps in reducing the spread of diseases and improving overall herd health.
- **Behavior Analysis:** Understanding animal behavior is crucial for effective livestock management. Deep learning models can classify and predict behaviors such as grazing, resting, or social interactions. This information can be used to optimize feeding schedules, manage stress levels, and improve animal welfare.
- **Environmental Monitoring:** Deep learning can also be used to monitor environmental conditions such as temperature, humidity, and air quality in livestock facilities. By integrating data from various sensors, these systems can ensure optimal living conditions for the animals, thereby enhancing productivity and reducing mortality rates.

4) Auto-Encoder: Auto-Encoder algorithm is unsupervised that can resist channel disruptions. It maps input data from (x) to (y), ensuring that the transmitted information is recoverable with minimal error.

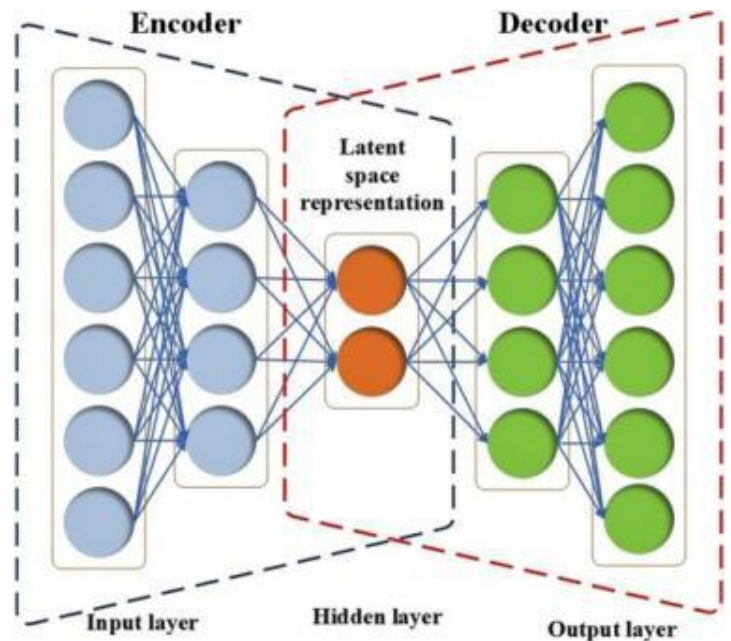


Fig. 2. Autoencoder Architecture

5) Performance Evaluation: In [29] ten CNN-related studies, Accuracy, Precision, Recall, and F1-score were simultaneously used as evaluation metrics. The four metrics are mainly used to measure the classification performance, and each is expressed as equations with True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). The formula is as follows:

Accurate Predictions: learning based on the neural network, and it helps to solve a wide range of tasks based on Artificial intelligent. Recent $Accuracy = \frac{TotalNumberof Prediction}{TotalNumberof Actual}$. (1) innovations coupled with the drone and Deep learning allow us to go much further and bring more precise information to the farmer by establishing real time zone control and collecting information to make the right decisions for livestock monitoring.

Managing animals on large farmland requires effective surveillance and monitoring. To achieve this, reliable communication between UAVs and a ground control station The following formula delineates the concept:¹

$$Precision = \frac{TP}{TP + FP}$$

II. METHODS

(GCS) is essential. Some tasks that auto-encoder can plays in livestock management:

- **Communication Strategies:** Auto-encoders are data- driven communication methods that facilitate interaction and data transfer between UAVs and the Ground Control Station (GCS). They learn mapping functions for both the UAV transmitter and the GCS receiver to support various communication techniques, such as QPSK, 8PSK, 16PSK, and 16QAM, without requiring prior knowledge.
- **End-to-End Communications:** The proposed deep auto-encoder framework for UAV design enables seamless end-to-end communication. Simulation results demonstrate the auto-encoder's ability to adapt to different communication strategies, making it a powerful tool for UAV-based livestock management.
- **System Design:** Imagine a UAV system designed for livestock farming management. It includes steps such as water analysis, planning a Long-Range Wide-Area Network (LoRaWAN), deploying drones with sensors and cameras, and optimizing drone flight paths.

The auto-encoder is designed for end-to-end communication, aiming to generate strong representations of messages. Prisma Methodology framework and Meta-Analyses will be used [56], this systematic literature Review aims to provide a comprehensive review of the current state of research on Livestock management and monitoring utilising Deep learning and Internet of Things. SLR is grouped into three different types: Planning, conducting and reporting the review of the smart farm. Search string design, database selection, exclusion and inclusion criteria.

A. Research Questions

To delve into the review study pivotal research questions are designed as following:

How can deep learning algorithms be optimized to enhance the accuracy and efficiency of animal monitoring and management systems, particularly in challenging environments such as vast rural areas or dense forests and How can advanced sensor fusion techniques be integrated with deep learning algorithms to enhance the accuracy and reliability of animal tracking and True Positive is represented by TP while False Positive is denoted by FP. TP represents features correctly predicted while the inverse is represented by FP.

Table II: some recent related studies

Authors	Topics	Methods	Limitations	Ref
Azizi et Al.	Deep Learning Pet Identification Using Face and Body	CNN	Processing Time, Hardware Constraints	[30]
Chen et al	UAV Camel Inspection System	Deep Learning, UAV	Object Detection, Localization, UAV Limitations	[31]
Aburasain et Al.	Object Detection and Recognition	CNNs, CCTV	High-Altitude Detection, Network Infrastructure, Positioning Accuracy	[32]
Gunaratnam et Al.	Computer Vision in Livestock Management	Computer Vision	Cost of IR Camera, Disease-Specific Limitations	[33]
Afwamba et Al.	UAS-Based Remote Sensing for Animal Detection	UAV	Timing of Data Collection, Ground Data Issues	[34]
Alvarez et Al.	Multispectral UAV for Pasture Depletion	UAV	Prediction Accuracy Decreases at Low/High Biomass	[35]
John Io Ojo et Al.	Remote Animal Monitoring System	Drone	Internet Stability, Cost-Efficiency Concerns	[36]
Ojo M et Al.	Smart Livestock Monitoring	IoT	Environmental Impact, Scalability Issues	[37]
Yang et Al.	Remote System for Echinococcosis Control	IoT	Interface Optimization, Data Adjustments	[38]
C. Martina et Al.	Predicting Parturition in Cattle	IoT	False Alarm, Sensor Tolerability Issues	[39]
Moniek S. et Al.	Computer Vision for Cattle Identification	YOLO5	Tag Quality, More Cameras Needed	[40]
Mahato et Al.	AI in Dairy Farm Management	CNN & DL	Data Collection, Technological Constraints	[41]
Mishra et Al.	IoT-Based UAV for Integrated Farm Management	DL & IoT	Unified Strategy, Predictive Capabilities	[8]
Tu et Al.	Depth Camera-Based Lameness Classification in Cows	Camera & DL	Dataset Size, Real-Time Processing	[42]
Yoon et Al.	Deep Learning Framework for Bovine Iris Segmentation	VGG16 & DNN	Model Selection, Potential Biases	[43]
Swain et Al	Smart Livestock Management Using IoT	ML	Data Quality, Technical Constraints, Implementation Cost	[44]
Kaswan et Al	Applications of Sensors in Livestock Management	AI & IoT	Accuracy Issues, Training Requirements, Early Adoption Challenges	[45]
Melak et Al.	AI Technology in Livestock Farms	AI	Data Acquisition, Limited Understanding	[46]
Ren et Al.	UAV Monitoring in Mining Areas	UAV	Sensor Limitations, Weather Dependency, Continuous Monitoring Challenges	[47]
Xu et Al.	Few-Shot Cow Identification via Meta-Learning	YOLO V5	High Labeling Costs, Data Scarcity, Model Training Time	[48]
Hamadani	AI in Animal Farms for Management and Breeding	AI, ML & IoT	Ethical Considerations, Sustainability Challenges, Data Privacy	[49]
C. He et Al.	Enhanced LiteHRNet-Based Sheep Weight Estimation	LiteHRNet & IoT	Posture and Lighting Variability, Model Overfitting, Limited Dataset	[50]
Li et Al.	Posture-Based Measurement Adjustment for Cattle	Cloud Data & CV	Posture Variability, Environmental Constraints, Cost and Complexity	[12]
Thakur et Al.	Digitalization of Livestock Farms	AI & IoT	Cost, Real-World Application, Specialized Training	[51]
Sharma et Al.	Deep Learning for Object Detection in Livestock	DL	Imbalance Sampling, Localization Challenges	[52]
Andrew et Al.	Individual Identification of Holstein Friesian Cattle	CV & UAV	Detection Failures, Manual UAV Operation	[53]
Islam et Al.	IoT and UAV-Based Smart Farming Review	IoT	Transmission Distance, Communication Technology Limitations	[54]
Bello et Al.	Mask YOLOv7-Based Drone Vision System	YOLO V7	Small Object Detection, Dataset Limitations	[55]

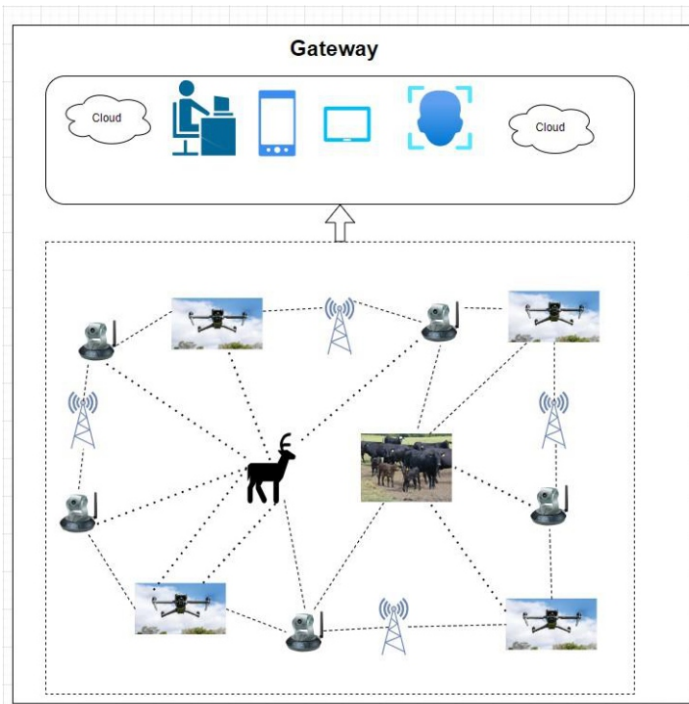


Fig. 3. Overview of livestock monitoring system using IoT and deep learning

1) monitoring systems, particularly in rugged or remote environments?

- Collect diverse training data by simulating various environmental conditions (e.g., different lighting, weather, and terrain).
- Pre-train models on related tasks (e.g., object detection) and fine-tune them for animal monitoring.
- Combine noisy sensor measurements (e.g., GPS, accelerometer) with deep learning predictions.
- Handle non-linearities and multimodal distributions in tracking, Ensure consistent measurements across sensors, and Combine predictions from multiple sources (e.g., vision and RFID tags).

2) What novel methodologies can be developed to integrate deep learning technology with anti-theft functions in animal monitoring systems, ensuring real-time detection and prevention of illegal activities such as poaching or livestock theft while minimizing false alarms and resource consumption? What are the most effective methods for optimizing deep learning models to detect anomalous behavior in animal movement patterns, enabling early identification of potential threats such as predator attacks or human encroachment?

- Train autoencoder neural networks to learn normal movement patterns and identify deviations;
- Combine predictions from multiple models (e.g., CNNs, RNNs) for improved accuracy;
- Apply attention-based models to focus on relevant features in the movement sequence, use LSTMs to model sequential animal movement data and detect anomalies.

3) How can edge computing architectures be leveraged to implement real-time decision-making capabilities in animal monitoring systems, allowing for rapid response to security breaches or emergencies without relying solely on centralized processing resources?

- Deploy edge devices (e.g., drones, cameras) equipped with GPUs or specialized accelerators near the monitoring area, Process AI tasks (e.g., object detection, tracking) directly on these edge devices, Edge devices can quickly analyze data without waiting for cloud-based processing.
- Combine edge computing with cloud resources, edge devices handle immediate processing (e.g., detecting intruders, emergencies situations). cloud resources manage data storage, manipulation, and visualization.
- Optimize deep learning models for edge deployment, Use lightweight architectures (e.g., YOLOv4, YOLOv7) suitable for edge devices, Accelerate inference using GPU-enabled edge devices (e.g., Jetson Xavier AGX).

4) What ethical considerations and privacy-preserving techniques should be prioritized in the design and deployment of deep learning-based anti-theft functions within animal management systems, to ensure minimal intrusion on wildlife and mitigate the risk of unintended consequences or misuse?

- Communicate to stakeholders (researchers, public) about the system's purpose, data collection, and potential impact;
- Prioritize the well-being of animals. Ensure that anti-theft measures do not harm or stress wildlife;
- Perform computations on encrypted data without crypton, Encrypt data during transmission between edge devices and central servers;
- Implement fail-safe mechanisms to prevent unintended consequences (e.g., false alarms causing panic);
- Harden models against adversarial examples that could mislead anti-theft functions.

B. Search Technique

The search technique used results in the choosing papers that are relevant to the range of the systematic literature review, and the search starts with key words between March and Jun of 2024. The databases search engine such as Consensus io , Scopus, Data and IEEE Xplore are considered for this SLR. In addition, others databases were also considered to cover a wide range of relevant content to ensure comprehensive results, database Google scholar ACM, Web of Science and Springer. selected research papers were limited according to the research field, such as computer science, computer engineering, and electrical engineering, and the date was from 2019 to June 2024. Nota: The editors also selected some papers from previous years. The initial search began with a comprehensive search query that covered a wide range of the relevant terms through the different databases cited above in order to cover a large range of the keywords are selected based on the recent publication in this area of research. "Computer vision" AND "Animal management" or "Image processing" AND "pig monitoring" or "cattle management" AND "Deep learning or machine learning" or "UAV" or IoT AND "Animal identification" "Pig" "classification" detection" or "cattle" OR "livestock" "identification" OR "recognition" OR "detection" OR "behavior" OR 'health'. In addition, the total of search from different database are 764. To filter out irrelevant sources, we applied additional restrictions as outlined. Specifically, by utilizing the 'LIMIT-TO' keyword in Scopus and following the proposed criteria, the results were reduced to 75 for Scopus, IEEE Xplore to 57 and 14 for Consensus. Our focus remained on journal articles published in English between 2019 and mid-Jun 2024. For more details based on this topic few related studies were rediscovered from the search result to extract the synonym and

key words by going through the title, abstract, field of studies, year of publication and authors.

1) Search Technique content: Given the extensive volume of collected papers, a comprehensive full-text analysis was impractical through the abstract. Instead, during this phase, we assessed the papers based on their abstracts, titles, and keyword lists. The inclusion and exclusion criteria, outlined below, guided our selection process. Consequently, a paper advanced to the next phase if it satisfied all inclusion criteria, while any meeting at least one exclusion criterion was excluded.

C. Selection Approach

In order to select the papers due to a large of full-text and the csv file exported from the the database, at this stage we went through each paper base on the abstract content to see if the paper is related to research. the inclusion and exclusion process used at this point to met requirements of this review. if not the paper will be deleted from the database selected in the excel sheet.

1) Inclusion Approach : The following approach's is used to select the paper as:

- Studies not written English;
- Studies that we are not able to download the full study or paper;
- Studies written from social social sciences field and informatics;

2) Exclusion Approach:

- Studies on smart farms;
- studies of Artificial intelligence or Deep learning or Machine learning or Convolution Neural network, computer vision based on livestock management using Internet of Things (IoT);
- Studies in the field of computer system engineering, computer science, sensors, Engineering;
- studies published between 2019 and Jun 2024;
- The finding were limited to journal articles.

III. REVIEW OF EXISTING WORKS

The goal of this study is to conduct a systematic review focused on the identification, detection, and traceability of dairy animals. In large areas, traceability is achieved using a unique identifier, which could be a man-made marker, device, or a natural characteristic that the animal possesses. Common methods for identifying individual cows using artificial markers include ear notching, ear tagging, and branding. The ear-notching technique involves cutting specific parts of the cow's ear, with each animal being identified by the location of the incisions [48]. Animal identification is a fundamental requirement for record-keeping and effective farm management. Sensors can collect essential data, which can then be shared with other devices or management systems through IoT and AI technologies. This approach helps streamline livestock farm management by reducing the need for manual labor in various routine tasks, such as detecting estrus, identifying sick animals, monitoring growth, maintaining records, managing culling, milking, and feed formulation and distribution [45]. A deep learning method was employed to automatically identify and track individual dairy cows from surveillance video. The researchers utilized a Faster R-CNN algorithm to detect the cows in the footage, and then trained a CNN to recognize each

cow based on its distinct characteristics [57]. Animal identification involves distinguishing each animal individually, enabling the monitoring and tracking of each one separately. This process serves various purposes, including record-keeping, effective farm management, ownership verification, biosecurity measures, registration, insurance, and protecting has been a significant increase in the adoption of new technologies. However, PLF technologies do have some drawbacks. Since these technologies are designed by humans, they are often limited by predefined parameters for detecting specific issues (such as tail biting), and as a result, may carry a degree of subjectivity [65]–[67].

PLF technologies, tailored for livestock management, allow for real-time tracking and automated regulation of animal productivity, health, welfare, and environmental impacts. These systems, which use sensors, cameras, or microphones, can send alerts directly to farmers through connected devices such as phones, computers, or tablets when anomalies are detected, enabling early intervention. Research highlights the significant potential of these 'smart technologies' in supporting livestock farmers with animal welfare monitoring, and several countries are already investing in their development, recognizing their role in advancing sustainable agriculture [68]–[70].

TABLE III

SEARCHING KEYWORDS THROUGH DIFFERENT DATABASE

Database. Keywords No. of Articles animals from theft. Additionally, livestock identification is required by regulatory authorities to ensure safety, traceability, and improve product quality [49].

As a result, many recent studies utilize two-dimensional (2D) camera monitoring, which offers a wider perspective, is cost-effective, and requires less computational power. Research has been conducted using 2D video-based monitoring to provide visual data, such as the collective detection of golden shiner fish groups [?], [58], [59]. High-resolution Scopus TITLE-ABS-KEY ("Animal Identification" OR "cattle identification" OR "cow* identification" OR "livestock identification" OR "cattle recognition" OR "cow* recognition" OR "livestock recognition" OR "cattle detection" OR cattle Tracking OR "cow* detection" OR "livestock detection") AND ("Artificial Intelligence" "deep learning" OR "machine learning" OR "neural network" OR "image processing" OR vision) AND ("Management" OR "Monitoring") AND ("Internet of Things" OR "Drone" OR "DJI" OR "Camera" OR "Wearable Device"). It was used to search in the title (TITLE), abstract (ABS) and 490 cameras can be attached to drones, but the performance of the IEEE keywords (KEY).model may be affected by natural factors like camouflage, perspective, high altitudes, obstructions, variable environmental conditions, inadequate lighting, overexposure, and dynamic, cluttered backgrounds [60]. Challenges in tracking animals in the field include factors such as small or varying animal sizes, changes in appearance, obstructions, limited recording availability, fluctuating lighting and shadows, and an unpredictable environment with an expansive, potentially limitless area where the animal might travel [61], [62]. To overcome these challenges, a reliable detection and tracking algorithm ("Animal" OR cattle OR cow* OR livestock) AND Xplore (identification OR recognition OR detection) AND ("deep learning" OR "machine learning" OR "neural network" OR "image processing" OR computer vision) AND ("Management" OR "Monitoring") AND ("Camera" OR "Wearable Device" OR "Drone" OR "DJI*") (anywhere).

Consensus "((("Artificial Intelligence" OR "Deep Learning" OR "Computer vision" OR "Image Processing" OR "Neural Network") AND ("Animal" OR "Livestock" OR "Cow*" OR "Sheep") AND ("Management" OR "Monitoring")) AND ("Internet of Things" OR "Drone" OR "DJI" OR "Camera" OR "Wearable De 174 100 is needed, one that operates with minimal constraints. For instance, a camera with unrestricted movement is essential to track animal paths in environments of varying sizes [62]. Precision Livestock Farming (PLF) for ruminants in grazing and foraging systems poses unique challenges, especially on large, remote properties with vast land areas and significant livestock populations [63]. Carefully monitoring cattle's feed intake provides a useful method for assessing their overall health. A reduction in feeding time can be a sign of illness. Additionally, the constant chewing associated with rumination is crucial for proper digestion. A healthy cow usually spends 500 to 600 minutes per day ruminating [64]. Challenges, there vice")) total -764.

IV. DISCUSSION

Effective livestock management and monitoring are vital aspects of the farming industry, especially when it comes to understanding animal behavior. Traditional methods often involve manual observation and record-keeping, which can be time-consuming and prone to errors. However, with the rise of deep learning and advanced technologies connected through the Internet of Things (IoT), there has been a significant shift.

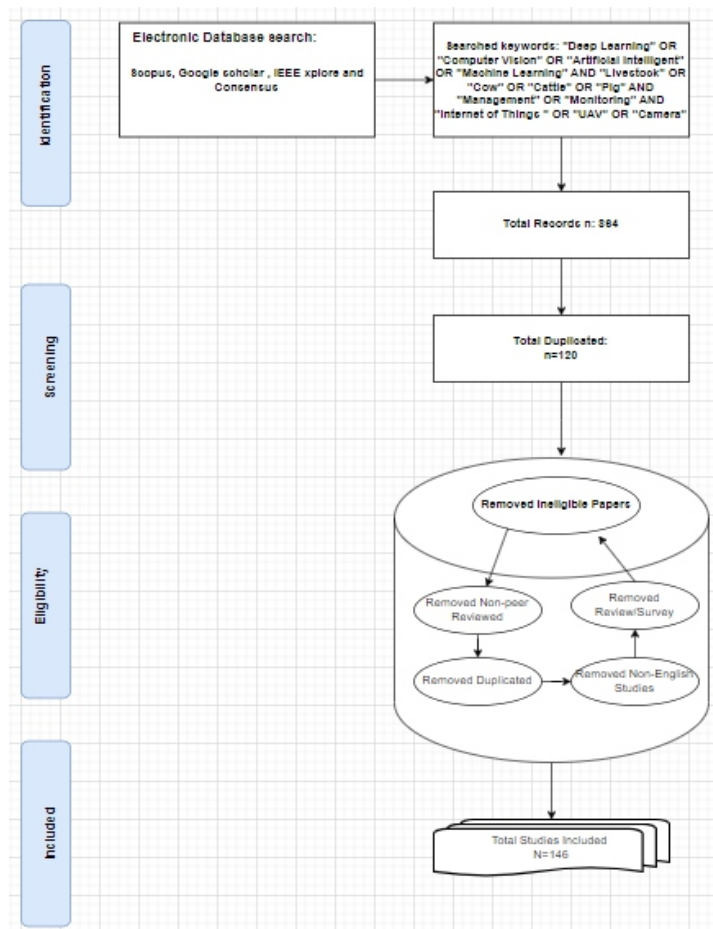


Fig. 4. Prisma diagram toward more automated and accurate systems for managing livestock.

Although numerous studies exploring computer vision and IoT technologies have shown promising results in improving livestock management, there is still a need for a comprehensive end-to-end approach. Many current methods rely on frame-by-frame object detection, using models like YOLO, R-CNNs, and CNNs to track animals and monitor their behavior through videos or camera traps. However, most of these studies use custom datasets collected from various farms under different conditions, which are not publicly available. This lack of accessible data creates challenges in developing robust deep learning (DL) models for recognizing livestock behavior.

To move forward, it is essential to develop public datasets that focus on specific animal behaviors, which would allow the research community to contribute more effectively. Additionally, there is a lack of standardized definitions for animal behaviors, leading to discrepancies in how behaviors like 'walking' are described. For example, 'walking' can refer to various actions, such as moving while standing, having the head raised, or continuous leg movement for several seconds. These definitions often stem from personal observations rather than expert assessments. To improve consistency, creating a uniform set of definitions for each behavior in collaboration with veterinary experts would be beneficial. This would lead to more reliable data collection and the development of DL models that can be compared on a common foundation.

Another challenge is that none of the studies reviewed have made the data they used to train their DL models publicly available. Sharing this data would allow researchers to test alternative approaches and ensure that results can be replicated. Finally, this systematic literature review (SLR) focuses on studies published between 2019 and October 2024, with articles selected from major research databases based on specific criteria. Other databases and research questions, particularly related to training and optimizing algorithms, were not covered in this review due to their scope.

V. CONCLUSION

This study aimed to explore how Deep Learning (DL) and the Internet of Things (IoT) are transforming farming into a smarter, more efficient industry. To achieve this, we reviewed various studies and products in the field. We found that AI technology is playing a significant role in helping farmers with a range of tasks, including device management, animal healthcare, security, and detection. AI-powered solutions also enhance activities like activity recognition, data processing, decision-making, image recognition, and even voice recognition.

However, there's a gap between the advancements in academic literature and real-world products. Many products on the market tend to focus on simpler applications like image and voice recognition. On the other hand, the literature often addresses more complex methods, such as activity recognition and predictive analytics. While AI technologies like voice and image recognition are widely adopted in smart farming products, there is still significant development needed for more sophisticated technologies, such as activity recognition, data processing, and prediction-making.

This study also highlights the importance of AI in making farms smarter, particularly in areas like device management, health monitoring, weight management, security, and decision-making. Emerging technologies such as AI, computer vision, machine learning, and UAVs (drones), along with IoT tools like smart collars, ear tags, and camera-based recognition systems,

are becoming essential in smart farming. However, as promising as these technologies are, there's still a need for further development in activity recognition and predictive systems. The insights provided by this literature review are crucial for advancing livestock management research. They help both scholars and farmers stay up-to-date with new trends and technologies, enabling them to make informed decisions both in research and day-to-day farm operations. Wearable devices are increasingly integrated into smart farms, allowing seamless connections with gadgets like smartphones, smartwatches, and computers. These innovations are fueled by advances in low-power chips, better connectivity, and real-time tracking and detection systems. Deep learning and wearable devices hold immense potential to revolutionize livestock management. By automating tasks such as animal identification, health monitoring, and behavior analysis, these technologies can improve farm productivity, enhance animal welfare, and reduce operational costs. However, addressing challenges like data quality, computational resource needs, and system integration will be key to ensuring the widespread adoption of deep learning in agriculture.

VI. CONTRIBUTION

In this study, we explored how deep learning and Internet of Things (IoT) technologies are being applied to modern livestock management. By reviewing 50 recent and relevant research papers, we examined how these tools are used in key areas such as animal identification, tracking, health monitoring, and anti-theft systems. We organized the findings based on the types of models used like CNNs, RNNs, LSTMs, and SVMs and how they function in practical farm settings. Through this analysis, we highlighted where these technologies are making a strong impact, and where they still face limitations. By identifying common trends, model choices, and technical gaps, this work provides a well rounded overview that can guide researchers, developers, and practitioners working in smart farming and precision livestock management.

VII. FUTURE SCOPE

Looking ahead, there are several promising directions for future work. One of the most pressing needs is the creation of open, standardized datasets that reflect diverse species, farm conditions, and animal behaviors resources that are currently lacking in the field. There's also a growing demand for lightweight AI models that can run efficiently on edge devices in rural or resource-limited settings, without depending on constant internet connectivity or high processing power. Real-time and scalable systems will be essential for monitoring large herds across wide geographical areas. Additionally, integrating data from multiple sources such as video, audio, motion, and temperature sensors can lead to richer, more accurate insights into animal well-being. As data collection increases, so does the need for privacy-preserving and secure systems to protect sensitive farm information. Lastly, future solutions should be flexible and adaptable to meet the unique challenges of local farming practices, environments, and regions. These areas represent exciting opportunities to make smart livestock monitoring more inclusive, effective, and sustainable.

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