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Integration of Machine Learning, IoT, and Geofencing for Livestock Management: A Review

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Abstract
An essential part of agriculture is livestock management, which calls for effective animal tracking and monitoring to guarantee the production, health, and well-being of the animals. Livestock management is one of the areas in agriculture that has made a substantial contribution in the global GDP. More to that, a lot of households around the world generate a lot of income from sales of meat, dairy, milk, butter, cheese, wool, hides and other by-products. In numerous regions, the practice of livestock farming is not merely an economic venture; it has deep cultural and traditional significance. It is at the heart of the identity and livelihood activities for many, how indigenous peoples, pastoralists and farming communities are resilient. Also, in much of the world, especially in pastoral systems that support diverse cultural landscapes and ecosystems, livestock play a role in biodiversity and maintaining land use. The field of livestock management has changed as a result of recent developments and technological innovations in Artificial Intelligence (AI), more especially machine learning (ML), the Internet of Things (IoT), and geofencing technologies. These technological innovations improve productivity, reduce disease transmission, and enable more sustainable and efficient livestock farming. Several studies have proposed various schemes and techniques for livestock management. This study presents a comprehensive review of the state-of-the-art AI schemes used in solving most of the issues related to livestock management and examines the advantages, difficulties, and potential future directions of combining ML, IoT, and geofencing for cattle management.

Keywords: *Machine Learning ML, IoT, Geofencing, Virtual Fencing, Livestock Management.*

1.0 Introduction

Livestock management has been completely transformed by the combination of ML, IoT, and geofencing technologies, which enable real-time tracking and monitoring of animals. IoT data can be analysed by ML systems to categorise animal activity, identify health abnormalities, and forecast animal behaviour. Real-time tracking of an animal's location, health, and behaviour is made possible by Internet of Things devices like GPS, RFID, and sensors. To track animal movements, identify breaches, and automate fence systems, geofencing technology establishes virtual borders. Nonetheless, the use of technologies like IoT in agriculture can have the most meaningful impact. Intelligent agriculture based on IoT technology will allow farmers and ranchers to reduce waste and increase productivity. [1]. Virtual Fencing in livestock management is essential for location and movement control, yet with conventional methods it requires close labour supervision, leading to increased costs and reduced flexibility. Consequently. Virtual fencing systems (VF) not long ago it gained noticeable attention as an effective method for the maintenance and control of restricted areas for animals. Existing systems to control animal movement use audio followed by controversial electric shocks, which are prohibited in various countries. [2]. A Virtual Fencing (VF) system is a digitalized method with embedded features to create non-physical boundaries of custom geometric size and shape without any physical fences or walls. This study uses VF (or Fenceless) systems, which have gathered momentum over the past three to four decades due to their salient advantages over traditional systems in Animals [2]. Large farm owners can utilize wireless IoT virtual fence applications to collect data regarding the location, well-being, and health of their cattle. This information helps them in identifying animals that are sick so they can be separated from the herd, thereby preventing the spread of disease. It also lowers labour costs as ranchers can locate their cattle with the help of IoT-based sensors.[1]. The emergence of advancements in virtual fencing technology, more or less the eShepherd virtual fencing system by Agersens Pty Ltd. This system uses licensed intellectual property developed by the Commonwealth Scientific and Industrial Research Organisation (Lee, 2006; Lee et al., 2007, 2009, 2010) and has been commercialised for cattle purposes. Virtual fence location is allocated using global positioning system (GPS) devices and communicated to cattle via neckband-worn devices. The Neckband devices replace the visual cue of an electric fence with a benign audio cue, which, if ignored, is accompanied by aversive electrical stimulation (Lee et al., 2018). Application of this stimuli sequence in response to animal behaviour enables cattle to avoid receiving electrical cues by learning to stop moving or turn away from virtual fences when an audio cue is emitted. Adoption of the eShepherd virtual fencing system into pasture-based dairy systems requires investigation. Pre-commercial prototypes of this system have been used to control the location of small groups (n ≤ 20) of grazing dry cattle even when virtual fences were moved (Lee et al., 2009) [3].

Our research is focused on virtual fence, but notwithstanding, we also added other parameters, such as monitoring the environmental, climate and health conditions of livestock using ML algorithms. Our IoT-based intelligent farming system is designed not only as a replacement for traditional systems, but it is also the new harness to uplift other growing or general in precision agricultural trends, such as organic farming and to increase transparency in agriculture. Unlike previous studies, experiments were conducted by the researchers over a large area to exclude the potential use of a virtual fence as a spatial grazing technology for livestock.[1]

2.0 Machine Learning

Machine learning is a subfield of Artificial Intelligence (AI). The goal of ML generally is to understand the structure of data and fit data into models that can be understood and utilised by people. Machine learning (ML) is a multidisciplinary approach (integration of computer science, engineering and mathematics) mainly used for data analysis, classification and pattern recognition. To measure the performance of ML algorithms and models, different statistical tools are applied, just as humans; ML also learns from data and past experience, and then it makes predictions based on them. [4]

2.1 Definition

Machine learning (ML) is a discipline of artificial intelligence (AI) that provides machines with the ability to automatically learn from data and past experiences while identifying patterns to make predictions with minimal human intervention. ML algorithms can analyse IoT data to predict animal behaviour, detect health anomalies, and classify animal activities.[5]

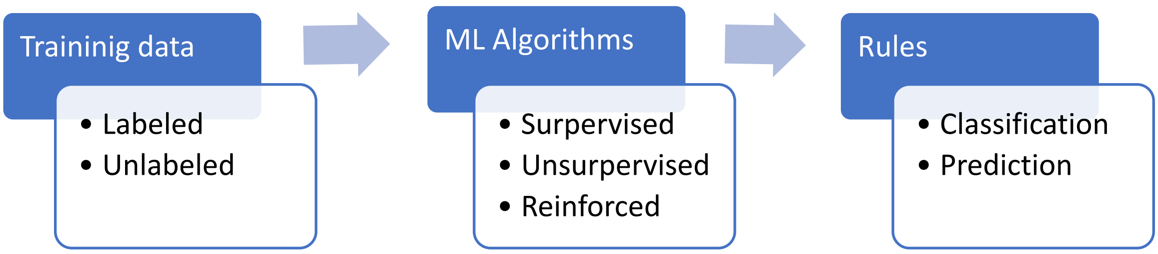

Figure 1: Typical process flow diagram in machine learning (ML) approach

2.2 Internet of Things

Internet of Things (IoT) is an extremely exciting set of technologies that is already shaping the future of humankind. IoT is based on the concept of uniquely identifiable interconnected devices (such as sensors, computers, and mechanical devices), collecting the data, and storing it in the cloud that is processed by intelligent algorithms to achieve common goals. IoT has several applications in almost all domains of life [6]. In the upcoming years, IoT-based technology will offer advanced levels of services and practically change the way people lead their daily lives. Advancements in medicine, power, gene, therapies, agriculture, smart cities, and smart homes are just a few of the categorical examples where IoT is strongly established [7]. IoT is a system of interrelated things, computing devices, mechanical and digital machines, objects, animals, or people that are provided with unique identifiers. And the ability to transfer the data over a network requiring human to human or human to computer interaction IoT devices (GPS, RFID, sensors) enable real-time monitoring of animal location, health, and behaviour as well other activities of the animals. Cow identification on farm is frequently achieved by Radio Frequency Identification (RFID) technology. In some research studies [8]. The possibilities of using different indoor positioning systems for tracking individual cows have been investigated. Such as Wireless Local Area Network technology for cow positioning performed with Bluetooth wireless technology, obtained an accurate result [9]

2.3 Geofencing

The technology of virtual fencing systems based only on sound is not new; however, it has been mostly applied to cattle. Studies of virtual fence systems for sheep solely based on sounds are limited, and most of them have used a combination of auditory warning and electric stimuli to train the animals. It has been reported that training animals using an electric stimulus could have a negative impact on their welfare, and this has led to their use on sheep being made illegal, as is the case in the UK. [2]

Virtual boundaries can be created to monitor animal movement, detect breaches, and automate fencing systems. Livestock monitoring is another important aspect of farming. Traditionally, cattle were monitored

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manually and confined in farms by building physical fences [10]. However, advanced technologies have made it possible to track and monitor the cattle automatically. Navigation satellites and Global Positioning System (GPS) are extensively used for tracking the position of cattle. UAVs have made real-time monitoring of cattle a cost-effective and hassle-free task. Radio-frequency identification (RFID), wireless sensor networks, and the Low Power Wide Area Network (LPWAN) are other potential technologies for establishing virtual fences to keep the farm animals in a confined area [6].

Figure 2: An imagery of Study Area

2.3.1 Types of Geofencing

1) Circular geofence and radius geofence are terms used interchangeably to describe a virtual barrier around a specific geographic spot, with a centre point and radius determining the geofence'sperimeter. Location-based services, asset tracking, and security applications all depend on circular and radius geofence.While radius g eofence concentrates on distance from the central point, circular geofence stresses shape, allowing for more effi cient monitoring and interaction.

2) Polygonal Geofencing: is a technique that creates a virtual barrier by connecting multiple geographic points with straight lines, allowing for more intricate and irregularly shaped areas like city blocks, parks, or property Boundaries. When devices enter or leave a designated area, polygonal geofencing initiates actions or notifications. This technology is helpful for location-based marketing, urban planning, and environmental monitoring for accurate border management.

3) Latitude and longitude geofencing is a method that uses precise geographic coordinates to create virtual boundaries, allowing for accurate location tracking and global boundary definition. Latitude and longitude geofencing is a technique that uses precise geographic coordinates to establish virtual borders, enabling accurate location tracking and global boundary definition. Latitude and longitude geofencing uses coordinates for asset tracking, location-based services, and targeted advertising, enabling businesses to monitor vehicles [11]. movement and notify clients when entering designated areas. Automobiles inside specific geographic boundaries.

All things considered, this method improves the capacity to work with and efficiently handle spatial data

3.0 Related Work

In order to give readers a thorough grasp of the state of the art, particularly with regard to livestock managemen, this section examines recent research on integrating IoT, machine learning, and geofencing. It focuses on studie s that do just that. Each summary briefly highlights the main findings, methodology, dataset, strengths, and weak nesses of the study. The simple concept of smart farming is the use of location devices as well as equipment to track livestock movements and sounds. The device sounds an alarm when an animal crosses the farm or trespasses on the restricted boundaries. Moreover, the farm animals' health and welfare may be tracked using IoT devices. IoT technologies that provide real-time location data, including wireless transmission and GPS tracking.

According to (Xi et al., 2024), the approach used is Support Vector Regression with a high-resolution grazing intensity dataset for the Selinco region for prediction of intensity; however, it is important to note that the complexity of the model can lead to underfit or overfit. In their 2023 study, Long et al. highlighted the SVR algorithm employed for the prediction of quantitative traits in dairy cattle Milk, while only specific species and not to others. According to [12], the method used in the paper is SVR for predicting models that improve agricultural output forecasts by reducing data volatility, enhancing prediction stability and accuracy. Utilizing support Vector Machine Muminov et al. (2019), who proposed two notable applications of machine learning in this context: animal behaviour prediction and activity recognition, particularly using Support Vector Machine (SVM) algorithms. Animal livestock audio stimuli in controlling crossing of virtual boundary Kleanthous et al. (2022), the

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use of audio stimuli can create a virtual fence for livestock using classification conditioning principles. As demonstrated by [13], who used audio stimuli that allows for non-invasive training that can enhance animal welfare and management, while zero control in mesh network in times of efficiency of detecting boundary breaches. According to [3], who used Logistic Regression that successfully used virtual fencing to contain dairy cows within designated boundaries, while the virtual fence is not as effective as electrical shocks that stop animals from crossing the line. According to [14], who used a generalized linear model (GLM) for cow statistical analysis, while Sample size and duration of the study may limit the generalizability of the findings.

In their 2023 Versluijs et al. (2023), who used Random Forest. Supervised machine learning for Successful classification of various cattle behaviours, including rare ones and it yield a high accuracy. On the other hand, the Sensitivity to data smoothing (running mean) for certain behaviours. According to (Ambrosio et al 2016), the novel approach for using machine learning to analyse animal behaviour in livestock monitoring is: however Limited experimental data due to the small number of animals and short duration of the study. Utilizing YOLOv5, YOLOv8 Ong et al. (2023), who used YOLOv5, YOLOv8 Tracking ByteTrack, BoT-SORT Pose-Estimation HRNet as their techniques for tracking the livestock, mean while, the tracking and pose estimation are still challenging tasks.

According to (Ilyas & Ahmad, 2020), who used IoT as a comprehensive solution for remote livestock tracking and geofencing, whereas The impact of environmental factors on sensor performance is acknowledged but not fully addressed. Animal individual tracking system c. Ren et al. (2021), who used Computer Vision and a Recurrent Convolutional Neural Network with embedded system that could track individual cows using Ultra-wideband technology, but the study has a limited dataset size. According to (Yamsani et al., 2024), who used Machine Learning algorithm that is Decision Tree and IoT sensors for Real-time monitoring, anomaly detection, resource optimization, No benchmark dataset, scalability limits. According to [15], who used Naïve Bayes multinomial (NBM), lazy IBk, random forest (RF) for Real-time livestock tracking using IoT Integration with cloud and Android app; however, although 2,000 samples is decent, it may not fully capture the variability across different regions.

According to (Olaniyi et al., 2024), who used IoT-UAV system for real-time cattle health monitoring, while Limited scalability for larger herds in vast terrains.

According to (Hamidi et al., 2023), who used Red-Green-Blue Vegetation Index (RGBVI) Unmanned-Aerial-Vehicle (UAV) Virtual Fencing (VF) Combines virtual fencing with remote sensing in a grid-based system; however, results may not be generalizable across different environments. According to (Swain et al., 2024), who Trained and compared five ML classifiers (RF, SVM, Lazy-IBk, PART, NBM), ensemble learning tackled feature complexity and overfitting, while the study did not explore regression-based prediction.

According to (Cihan1 et al., 2025), who used Fuzzy C-means, K-means, and Level-set SIFT, SURF, BRISK, FAST, and HARRIS, applied biometric identification and recognition process using retinal images taken from both eyes, but it lacks external validity due to a restricted testing environment and sample of the dataset. According to (Kaur and Virk, 2025), who used Machine Learning: Random Forest, Support Vector Machines, K-Nearest Neighbour, Naïve Bayes, and Decision Trees and IoT for 150 cows, capturing different parameters to detect anomalies and patterns indicative of various health conditions, while relying on physical sensors that are highly vulnerable to Movement, weather, and Time.

According to (Araújo et al., 2025), who used YOLOv8 with CBAM for monitoring and its outperformed YOLOv8 by 2.3% in mAP across all camera types, achieving a precision of 95.2%, however, the study lacks of automated health monitoring, behavioural analysis and tracking within a smart farm management system. According to (Wang et al. 2025), who used Multi-sensor data fusion, signal analysis, and machine learning for dimensionality reduction of behavioural data, the Behavioural misidentification of a cow standing still causes inaccuracies.

While early virtual fencing frameworks primarily relied on linear statistical models to assess animal response to audio stimuli, recent advancements have increasingly integrated non-linear Machine Learning (ML) classifiers to interpret complex behaviour patterns. For example, Support Vector Machines (SVM) have been widely deployed for activity recognition due to their efficiency with smaller, high-dimensional datasets. However, SVM algorithms suffer from computational bottlenecks when applied to continuous, high-frequency IoT streaming data. To overcome this limitation, recent studies have favoured ensemble approaches like Random forest and Deep Neural Networks, which yield higher classification accuracy for complex behaviour dynamics, Albeit at the expense of greater 1.4. The Summary of the Research Articles is given in Table 1.

Table 1: Summary of the research articles

S/N	Author	Methodology	Dataset	Strength	Weakness
1.	[16]	Support Vector Machine Regression	High-resolution grazing intensity dataset in the	The study developed a highly refined	It is important to note that, the complexity of the

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S/N	Author	Methodology	Dataset	Strength	Weakness
			Selinco region China	SVMR leaning algorithm to predict a pixel level	model can lead to over fitting or under fitting
2.	[17]Wu, C., et al. (2023)	This study explores SVMR for predicting quantitative traits in dairy cattle and wheat, focusing on milk yield and grain yield	SVMR is implemented with kernel functions (not specified but likely RBF or linear), optimized for genomic prediction	Efficacy of SVR in handling intricate genetic interactions, demonstrating superior prediction accuracy compared to Bayesian Lasso, and highlighting the advantages of dense molecular markers.	The article examines how SVR models for wheat and dairy cattle have constraints, are computationally complex, and are difficult to interpret, making them difficult to apply to other species.
3.	(Kuan et al., 2022a) (Kuan et al., 2022b)	This paper proposes a hybrid Marriage in Honey Bees Optimization/Support Vector Regression (MBO/SVR) model to predict long-term agricultural output, including livestock and poultry production, in Taiwan	The MBO/SVR model combines SVMR with an optimization algorithm to minimize the impact of outliers	The machine-learning prediction model improves agricultural output forecasts by reducing data volatility, enhancing prediction stability and accuracy.	Because of its intricacy, lack of integration of external socio-economic elements, and focus on Taiwan's agriculture sector, the study's global relevance is limited.
4.	[1]	Support Vector Machines (SVM) And virtual fence system	Not Mentioned	SVM handles small and unbalanced datasets well and minimizes empirical classification error while maximizing geometric margin	The classification data is non-linear, which complicates categorization without the use of kernel functions
5.	[2]	Generalized Linear Model (GLM) for analyzing the effect of audio stimuli on sheep behavior.		The use of audio stimuli allows for non-invasive training methods that can enhance animal welfare and management.	The effectiveness may vary based on individual animal personality types and the specific audio frequencies used.
6.	[13]	Optimized Echo protocol for LoRaWAN mesh networks. Geofencing algorithm using GPS data	GPS data from LoRa nodes. Network performance metrics (packet collision rate, network throughput,	Scalable and energy-efficient for remote monitoring. Addresses challenges of limited cellular coverage.	zero-control mesh network to efficiently detect boundary breaches of the monitored subjects such as cattle

S/N	Author	Methodology	Dataset	Strength	Weakness
7.	[3]	Logistic regression for analyzing learning behaviour. Generalized linear mixed models	Data on cow behaviour, pasture utilization, and virtual fence interactions.	Successfully used virtual fencing to contain dairy cows within designated boundaries. Utilization within inclusion zones.	Virtual fencing is not as effective as electric fencing in preventing cows from entering exclusion zones.
9.	[14]	Generalized linear model (GLM) for statistical analysis		Successful demonstration of effectiveness of virtual fencing for managing Limousin cows. Provided insights into the learning process and adaptability of cows.	Sample size and duration of the study may limit the generalizability of the findings. Further research is needed to assess long-term effects on animal welfare and performance.
10.	[18]	Random Forest. Supervised machine learning. Behaviour classification.	Using accelerometry data	Successful classification of various cattle behaviours, including rare ones. Robust to collar placement variations. High accuracy, precision, and recall rates.	Accurate classification for rare behaviors (<0.1% of data). Sensitivity to data smoothing (running mean) for certain behaviours
11.	(Ambrosio et al 2016)	Machine learning IoT	Livestock monitoring dataset	Proposes a novel approach for using machine learning to analyse animal behaviour in livestock monitoring.	Limited experimental data due to the small number of animals and short duration of the study.
12.	[19]	Detection-YOLOv5, YOLOv8 Tracking ByteTrack, BoT-SORT Pose-Estimation HRNet, YOLOv8-Pose Segmentation YOLOv5,YOLOv8	CattleEyeView dataset	This dataset fills a significant gap in the literature. Annotations: The dataset includes annotations for various tasks,	The paper notes that tracking and pose estimation are still challenging tasks, even with the dataset
13.	[6]	IoT and geofencing		Proposes a comprehensive solution for remote livestock tracking and geofencing. Addresses the challenges of traditional livestock management methods.	The impact of environmental factors on sensor performance is acknowledged but not fully addressed.

S/N	Author	Methodology	Dataset	Strength	Weakness
S/N	Author	Methodology	Dataset	Strength	Weakness
14.	[9]	Computer vision module Recurrent Convolution Networks	Cows' negative and positive interactions were performed on foreground video stream	This research presents an embedded system that could track individual cows using Ultra-wideband technology mean error 0.39, standard deviation of 0.62 m	Limited dataset size: 1080 hours of video data might improve RTLS
15.	(Yamsani et al., 2024)	Decision Tree Machine Learning and IoT sensors	temperature, humidity, grazing patterns, and movements dataset	Real-time monitoring, anomaly detection, resource optimization	No benchmark dataset, scalability limits, missing performance metrics
16.	[15]	Naïve Bayes multinomial (NBM), lazy IBk, random forest (RF), partial tree (PART), and support vector machine (SVM)	A dataset of 2,000 samples from diverse cattle populations was amassed	Real-time livestock tracking using IoT Integration with cloud and Android app, sensor deployment Multi-algorithm ML classification	Although 2,000 samples is decent, it may not fully capture the variability across different regions, breeds, and farm conditions. Larger, more diverse datasets would improve generalisation
17.	[21]	IoT-UAV system for cattle health monitoring	Cattle health data	Innovative combination of UAVs and IoT for livestock monitoring. Real-time data with Kalman filtering. Energy-efficient standby	Limited scalability for larger herds in vast terrains. UAV endurance still a constraint. Reliance on BeiDou might limit global deployment
18.	[22]	Red-Green-Blue Vegetation Index (RGBVI) Unmanned-Aerial-Vehicle (UAV) Virtual Fencing (VF)	Provides a base to analyse and combine the different spatial datasets on fixed polygon locations	Combines virtual fencing with remote sensing in a grid-based system, which is novel and forward-looking for precision livestock management	Being a single case study, results may not be generalizable across different environments, livestock species, or management systems
19.	[15]	Trained and compared five ML classifiers (RF, SVM, Lazy-IBk, PART, NBM).	Used a real-world IoT dataset (2,000 samples) with cattle disease indicators	High accuracy with RF (88%). Ensemble learning tackled feature	Limited dataset size No exploration of regression-based prediction

S/N	Author	Methodology	Dataset	Strength	Weakness
				complexity and overfitting	
20.	[23]	Fuzzy C-means, K-means, and Level-set SIFT, SURF, BRISK, FAST, and HARRIS	Retinal Image Dataset	Applied biometric identification and recognition process using retinal images taken from both eyes	Lack of external validity due to restricted testing environment and sample size of dataset
21.	[24]	Machine Learning: Random Forest, Support Vector Machines, K-Nearest Neighbour, Naïve Bayes, and Decision Trees and IoT	150 dairy Cows dataset on health parameters	Machine learning algorithms analyse these data to detect anomalies and patterns indicative of various health conditions	Reliance on physical sensors that are highly vulnerable to Movement, weather, and Time
22.	[25]	YOLOv8 with the CBAM	diverse cow health dataset composed of six different environments, including indoor and outdoor scenarios	YOLOv8-CBAM outperformed YOLOv8 by 2.3% in mAP across all camera types, achieving a precision of 95.2% and an mAP@0.5:0.95 of 82.6%	Lack of automated health monitoring, behavioural analysis and tracking within smart farm management systems, enabling precise detection of individual cows
23.	[26]	Multi-sensor data fusion, signal analysis, and machine learning	Behavioural dataset, both estrous and non-oestrous behaviours	Principal component analysis (PCA) was used for dimensional reduction of behavioural data	Behavioural misidentification: a cow standing still, which causes inaccuracies

4.0 Methodology and PRISMA Framework

To ensure a rigorous and repeatable systematic review, this study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.

Database Search and searching style: Electronic database searches were conducted across IEEE Xplore, ScienceDirect, Google Scholar and Semantic Scholar. The search query combined Boolean operators targeting three core domains:

- (“Virtual Fencing” OR “Geofencing” OR “Fenceless”) AND (“Machine Leaning” OR “ioT” OR “Sensors”) AND (“Livestock” OR “Cattle” OR “Sheep”)

Inclusion and Exclusion Criteria:

- Inclusion Criteria:
  - Peer-reviewed Journal and Conference articles focusing on precision livestock farming.
  - Studies incorporating at least two interesting domains: IoT hardware, ML behaviour classification, or geofencing/virtual fencing algorithms.
  - Primary research presenting empirical data, sensor telemetry, or algorithmic models.
- Exclusion Criteria:
  - Studies focused exclusively on livestock overgrazing, the livestock applications (e.g geofencing, animal helth monitoring, animal behavioural activities, livestock intensity or overgrazing).
  - Review papers, non-peer-reviewed preprints, or studies lacking methodology details

Quality Assessment Checklist:

Select Primary studies were evaluated against a 4 points quality framework:

(i) Clear specification of sensor telemetry and hardware deployment.

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(ii) Explicit definition and validation metrics of the ML algorithms used.
(iii) Dataset transparency (sample size, trial duration and animal count).
(iv) Practical field implementation and theoretical simulation

The PRISMA Methodology flow Diagram

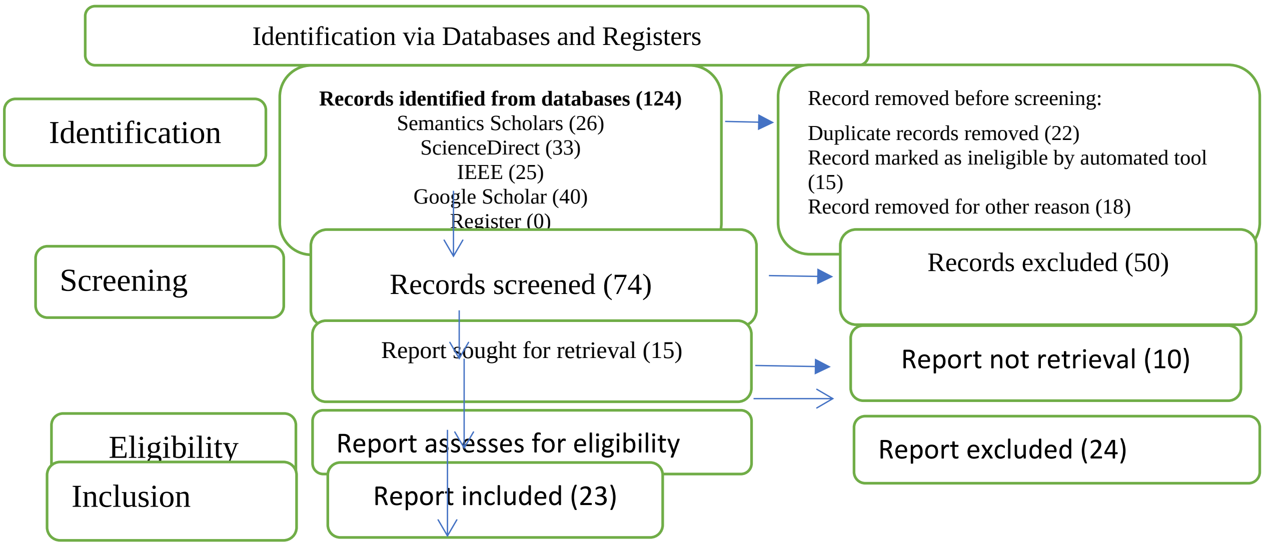

Figure 3: The PRISMA methodology flow diagram

The methodology used in this work is PRISMA, which is the Preferred Reporting Items for Systematic Reviews and Meta-Analysis, and was utilised to provide a framework that aids the systematic literature review, ensuring consistency with existing literature and fulfilling the objectives of this study. A study on IoT for problem-solving identified and eliminated duplicate articles using the PRISMA framework. After applying the inclusion-exclusion criteria, a qualitative synthesis of the included studies was carried out. A thorough analysis was made possible by the classification of relevant, partially relevant, little relevant, and other relevant studies. The systematic review process was streamlined using PRISMA, a database search, and other indexing databases like Semantic Scholar, Google Scholar, and Science Direct/Elsevier, IEEE etc for broader coverage. In this work 124 papers were Identified, 50 was removed based on certain criteria, remain 74 for screening, 49 eligible, remained 23 after going through Inclusion and exclusion criteria, in which after through going through using inclusion and exclusion criteria, then 23 were identified as once used in work.

4.1 Data Processing Platforms

Cloud, edge-computing, ML model deployment, and user interface. Successful implementations of ML, IoT, and Geofencing in livestock management have demonstrated improved animal tracking, enhanced grazing management, reduced livestock theft, automated health monitoring, and optimized feed management. During their operation, the collars sent a status report every fifteen minutes. Further, this report messages, contained: the date and timestamped GPS location including information about the total duration of the audio cues, steps taken by cows and the collar status (e.g., normal or escaped). Normally, these records are logged on server as raw data. In our case, they were provided, for scientific purposes, from the manufacturer. At the end of the experiment in total 33449 records were downloaded by the server in .csv format. These data were further processed to obtain more detailed information. In doing so, the entire data set was divided into three different categories of (1) data; stimuli delivered; (2) learning capacity; (3) VF ability to restrain cows, which the Coordinates of virtual boundaries and animals' GPS tracking were imported into GIS software, to recreate the spatial distribution of the cows among trials. Moreover, distribution heat maps were generated as well.

5.0 Synthesized Results and Discussion

Across the evaluated primary studies, integrating IoT neckbands with ML Algorithms significantly improved virtual fence compliance while safeguarding animal welfare.

Stimuli Response and Behavioural Adaptation: Synthesized metrics across trial indicate a clear learning curve in cattle and sheep exposed to virtual boundary cues. Across repeated exposure trials, the ratio of audio warnings to electrical stimuli delivered increased significantly, demonstrating that livestock rapidly learn to respond to benign auditory warning before reaching the virtual threshold.

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Behavioural Classification Accuracy: when pairing accelerometer telemetry with ML classifiers, multi-class algorithms (such as Random Forest and Long Short-term Memory networks) achieved high precision in distinguishing core behaviours (e.g grazing, resting, walking). This multi-sensor data fusion enables real-time anomaly detection, allowing producers to identify early stress indicators or escape attempts.

When analysing the integration of IoT, machine Learning and Geofencing, we find a range of perspectives, techniques and outcomes across the reviewed literature. By examining the key papers in this domain, the discussion and results aim to summarise the main findings. The paper highlighted common themes, important changes and emerging trends that shape the field of techniques precisely in livestock management.

The benefits have been discovered to include:

- Improved animal tracking, enhanced grazing management, reduced livestock theft, automated health monitoring, and optimized feed management.
- To maximize productivity, reduce cost, increase convenience, and environmental protection, agriculture is and has always been an industry that quickly adopts cutting-edge technologies, by leveraging into them will enhances the smooth flow of the system.

6.0 Challenges

Despite the benefits, several challenges persist, including data quality and reliability, energy efficiency and power management, scalability and cost-effectiveness, integration with existing systems, and cyber security concerns. Future research directions include integrating other technologies, such as block-chain and computer vision, developing sophisticated ML models for animal behaviour analysis, focusing on animal welfare and behavioural analysis, and expanding to other livestock management areas, such as aquaculture.

7.0 Conclusion

Integrating ML, IoT, and Geofencing technologies has transformed livestock management. While challenges persist the benefits of improved animal tracking, automated health monitoring, and optimized animal feeding management make this approach an attractive solution for farmers and ranchers. The future direction is going to integrate with other technologies such as block-chain, computer vision. Sophisticated ML models for animal behaviour analysis, such as Animal welfare, and expansion to other livestock management areas such as (aquaculture). This will go a long way in opening up the horizon to researchers to this field of research.

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