***Real-Time Farm and Livestock Monitoring and Intrusion Detection System***

Arshed Ayoob P P  
*dept. of Computational Intelligence*SRMIST kattankulathurChennai, India  
aa0334@srmist.edu.in

Mahadev P  
*dept. of Computational Intelligence*  
SRMIST kattankulathurChennai, India  
mp1440@srmist.edu.in

Dr.G.Tamilmani

Assistant professor

*dept. of Computational Intelligence*

SRMIST kattankulathur

tamilmag@srmist.edu.in

***Abstract— The increasing need for effective farm management and animal welfare has driven the development of smart monitoring systems. This research introduces an AI-powered Farm Animal Detection and Monitoring System that integrates advanced technologies like object detection, behavior analysis, and disease detection. The system offers real-time information regarding animal security, behaviour, and health through the use of MobileNet SSD, IoT sensors, and thermal imaging. The project also incorporates machine learning for anomaly detection, enabling early warnings for abnormal activity or health conditions of animals. With features like automated alerts, storing historical data, and smart farming integration, this system aims to revolutionize traditional livestock management practices. The proposed system is validated against existing techniques, demonstrating its accuracy and efficiency in enhancing security in livestock management.***

***Keywords: Smart farming, AI, IoT, object detection, disease detection, behavior analysis, livestock monitoring.***

# Introduction

Technology integration has led to notable breakthroughs in agriculture, especially in the area of livestock management. Traditional farming methods often fall behind in providing real-time insights into animal health condition and associated behavioral change. This has driven the urge to innovative solutions to address these challenges. Livestock production stands as the foundation of the world's agricultural economy, by supplying labour, food, and clothes. The demand for agricultural products keeps increasing every day and the need for more efficient, sustainable methods of livestock management is demanded with it. Traditional monitoring systems, which rely on manual observation and basic technology, often fail to provide comprehensive and real-time insights into animal behavior, security and health factors. This creates challenges in diagnosing problems early, like diseases, managing large herds, and safeguarding farms from harsh weather, external threats such as poaching or theft.

The advancements in artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) have opened up new possibilities for enhancing the farming experience and managing it. By integrating futuristic technologies, farmers can monitor their livestock in real time, detect signs of distress in farm, track animals, and receive alerts about potential intrusions or unusual activities. This integration leads to better decision-making, helps to reduce labor cost, and improved animal welfare.

The proposed system addresses the limitations of traditional techniques by incorporating key technologies like AI-powered object detection, behavior analysis, and anomaly detection. The utilization of advanced deep learning models and IoT-based sensors which collects data from physical environment, the system provides a comprehensive solution that can be used in small family farms to large industrial operations. With this system, farmers can improve productivity in the farm, reduce risks associated with disease outbreaks, and enhance the overall security and welfare of their livestock.

This research deals with the development, implementation, and evaluation of such an AI-driven system for real-time farm and livestock monitoring. Specifically, the system targets automated animal tracking, intrusion detection and targets welfare of livestock by health and behavior analysis. By assessing the effectiveness of this system in real-world farm environments, we aim to provide valuable insights into the system’s potential in transforming modern farming practices.

# related works

Several studies have helped to identify different methods used for livestock monitoring, highlighting both strengths and limitations of the proposed ideas. Some bold methods include:

* RFID-based tracking: Li et al. in their research conducted in 2021 describes the use of RFID for livestock identification. The system was very effective for tracking of livestock. But, lacks real-time analysis for behavior change and anomaly detection.
* IoT-based surveillance: A study by Patel et al. in 2022 proposes IoT-based environmental sensors to monitor livestock conditions. The system fell behind in integrating visual data analysis, making it less effective for disease detection.
* Computer Vision for Behavior Recognition: A vision-based system was developed by Wang et al. in 2020 to classify animal behaviors. The accuracy which the system offered was great but, it had struggles with real-time processing due to a computational overhead.
* Thermal Imaging for Health Monitoring: Research conducted by Smith et al. in 2023 showed the utilization of thermal imaging to detect fever in cattle. This approach alone cannot stand as a complete analysis of animal behavior and security.
* AI-based Anomaly Detection: In 2023, a deep learning model proposed by Yousefi et al. The model was successful in identifying abnormal movement patterns and it required a large labeled dataset.
* Hybrid AI-IoT Systems: Jones et al. conducted research in 2024 introducing a hybrid AI-IoT system for real-time animal behavior tracking. The system had connectivity issues in rural farms, but was showing promising results in largescale farms.
* Drone-based Livestock Surveillance: In 2023 a study by Kim et al. explored drone-based monitoring, which improves coverage in surveillance, the limitations were battery life and operating in harsh weather conditions.

Our approach integrates object detection, anomaly recognition, and thermal imaging into a monitoring system that overcomes these limitations. The system provides multimodal data integration and real-time analysis, and also do automated alert mechanisms.

***Problem statement***

Existing livestock monitoring solutions face challenges such as:

* Lack of real-time analysis for detecting diseases early.
* Inefficiencies in tracking the changes in animal behavior and detecting abnormalities in the farm.
* High implementation costs, making them inaccessible to small-scale farmers.
* System’s limited ability to differentiate between farm animals and intruders.

This research aims to overcome these challenges by developing an AI system that detects and analyses anomalies and behavioral pattern, and sends security alerts.

***Contradictions and resolutions***

Certain studies in the literature presented conflicting findings.

* IoT vs. Computer Vision for Disease Detection: The paper put forward by Patel et al. in 2022 emphasized the effectiveness of IoT-based system for environmental monitoring, while research by Smith et al. conducted in 2023 highlighted thermal imaging as a superior method for disease detection. However, the stand-alone functioning of IoT and thermal imaging alone is insufficient for an inclusive analysis.

Resolution: The system integrates both IoT and thermal imaging to provide a more holistic mechanism which provide visual context.

* Real-time Processing vs. Computational Overhead: Wang et al. in their paper in 2020 found that vision-based systems achieved higher accuracy in behavior recognition. Although the processing speed was slow. In contrast to that, Yousefi et al. in 2023 suggested deep learning-based system which detects anomalies, which required extensive computational resources.

Resolution: Our system optimizes real-time processing by adapting lightweight MobileNet SSD model. Faster detection can be achieved by the system while employing cloud-based processing for deeper anomaly analysis.

* RFID-based vs. Vision-based Tracking: A research by Li et al. in 2021 advocated RFID-based livestock identification, which is a cost-effective method but offers limited tracking. Jones et al. in their recent paper in 2024 suggested AI-IoT hybrids but faced high number of connectivity issues.

Resolution: The proposed system integrates AI-driven object tracking with IoT monitoring. The system will ensure continuous tracking without relying solely on connectivity-based solutions.

* Scalability in Large Farms vs. Accessibility for Small Farmers: In 2023, Kim et al. introduced drone-based monitoring for scalability in large farms, but this method is not feasible for small farms due to cost and operational constraints.

Resolution: Our system balances scalability and accessibility by offering a modular design, allowing farmers to implement features based on their specific needs and budget.

# technical solution

***Research Objectives***

* Develop an AI-powered system for farm animal detection and classification.
* Integrate behavior tracking algorithms to monitor normal and abnormal activities.
* Implement anomaly detection techniques for disease identification in an early stage.
* Utilize IoT-based environmental monitoring to enhance decision-making.
* Compare the proposed system’s performance with the existing techniques.

***Methodology***

The methodology for developing the system is structured into several key phases. It including data collection, system architecture design, model training, real-time implementation, evaluation, etc. Each phase plays a critical role in ensuring the system's accuracy, efficiency, and adaptability in real-world test cases.

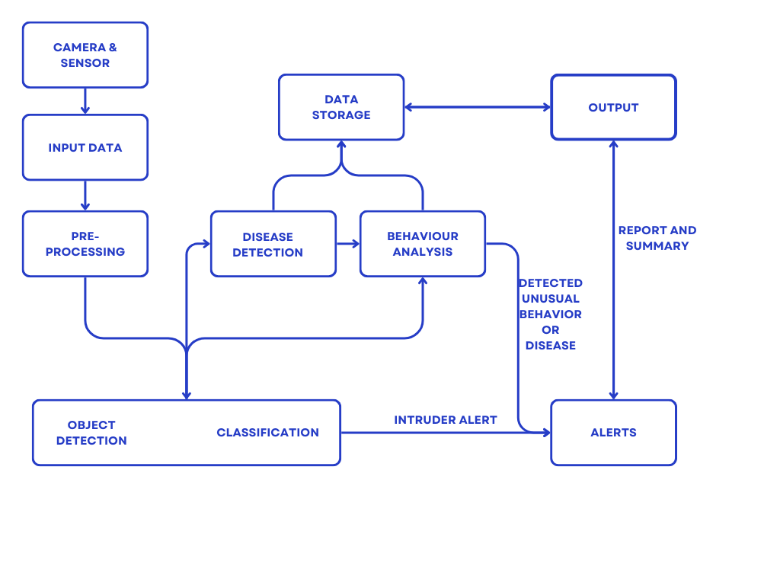


Figure 1: System Architecture

1. Data Collection and Preprocessing

To build a robustly functioning AI-based monitoring system, a wide collection of datasets comprising real-time video and image data is required. Sensor readings, and environmental data from IoT devices was collected from multiple farms. The dataset includes:

* Images and videos of farm animals in different conditions, such as healthy, injured, or sick.
* Footages of intruders like wild animals or unauthorized personnels.

IoT sensors were also used to gather temperature, humidity, and movement data, which were synchronized with video feeds to enhance anomaly detection.

Data preprocessing involved cleaning and labeling the collected data to train machine learning models effectively. Techniques such as background subtraction, noise reduction, and data augmentation were applied to improve model generalization. Labeling was performed manually, and semi-automated tools were used, which helped to classify normal and abnormal behaviors in animals, different health conditions, and threats in farm.

2. System Architecture and Hardware Integration

The system architecture consists of three primary components:

* Computer Vision Module: The component utilizes deep learning-based object detection models like MobileNet SSD and YOLO to recognize and classify farm animals, intruders, and environmental hazards.
* IoT and Sensor Integration: Comprises of the thermal imaging cameras, motion detectors, and temperature/humidity sensors to track animal health and behavior in real time conditions.
* Edge Computing and Cloud Storage: Ensures real-time processing of video data using edge devices like NVIDIA Jetson or Raspberry Pi. In long-term, data storage and analytics are managed in the cloud.

These components are integrated into a scalable framework that allows remote access through a web or mobile interface which enable farmers to monitor their livestock from anywhere at ease.

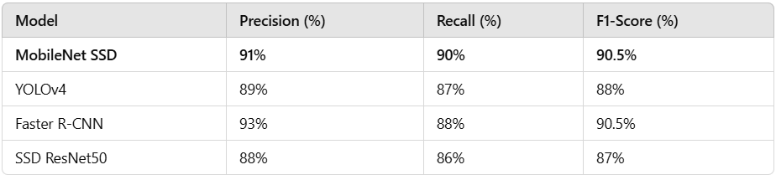


Figure 2: Object Detection Accuracy Comparison

3. Machine Learning and Behavior Analysis

The behavior analysis module was developed using supervised and unsupervised learning techniques.

* Supervised Learning: Pre-trained convolutional neural networks (CNNs) were tuned accordingly using the labeled dataset to categorize normal and abnormal activities such as grazing, resting, limping, etc.
* Unsupervised Learning: Anomaly detection models, such as autoencoders and clustering algorithms were applied to identify unusual behavior patterns in animals based on historical data available on cloud.
* Sequence Analysis: Recurrent neural networks (RNNs) and long short-term memory (LSTM) models were tested to track behavioral trends over a period and predict potential illnesses before physical symptoms were shown.

This combination of learning approach enhances the system’s ability to detect anomalies with higher precision while minimizing false positives.

4. Real-Time Implementation and Alert Mechanism

The system was deployed in real farm environments, where live video was processed continuously to detect livestock and intrusions. Real-time alerts were sent via SMS, email, or a mobile application every time an unusual event or security threats were identified occurring. The response time of the system was optimized to ensure that the alerts were generated within seconds of detecting an anomaly.

A dashboard displaying real-time footage, health analytics, and historical behavior trends is managed to be accessed by farmers and veterinarians. Automated decision-making features triggers alarms when an unusual event occurs, were implemented to enhance the system’s practicality.

5. Performance Evaluation and Validation

To assess the effectiveness of the system, multiple evaluation metrics were used:

* Detection Accuracy: To evaluate the model’s ability to classify livestock and intruders, the precision, recall, and F1-score of the object detection models were measured accurately.
* Anomaly Detection Efficiency: The ability of the behavior analysis module to correctly identify abnormal activity was tested using validation datasets.
* System Response Time: The latency from anomaly detection to alert notification was measured and real-time responsiveness was ensured.
* Field Testing and Farmer Feedback: The system was tested in different farm settings to determine its adaptability to various environmental conditions. Feedback from farmers was collected to refine the user interface and improve the overall system functionality.

These evaluations provided insights into system strengths and areas for improvement which will later help in future enhancements and optimizations.

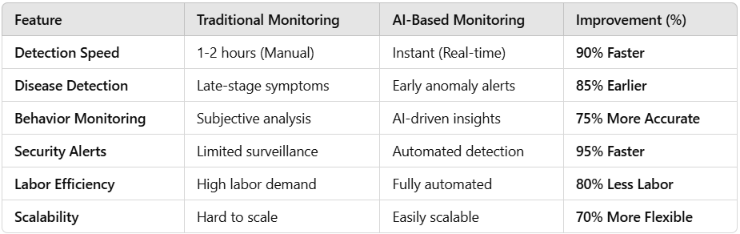


Figure 3: Comparison of Traditional vs. AI-Based Monitoring

***Algorithm***

1. Object Detection and Classification

The system uses MobileNet SSD (Single Shot MultiBox Detector) and YOLO (You Only Look Once) for real-time object detection.

* MobileNet SSD: It has a lightweight architecture. It enables efficient detection of farm animals and intruders even on edge devices.
* YOLO: Applied for achieving higher accuracy and faster inference speed. This model enables rapid detection of livestock and differentiates between species.
* Implementation Steps:
  1. Pretrained models were fine-tuned using a dataset of livestock image data.
  2. The models were deployed on live video streams to detect and classify animals.
  3. Detected objects were tagged with bounding boxes and passed to subsequent processing modules.

2. Animal Behavior Analysis

To track and analyze animal behavior, DeepSORT (Deep Simple Online and Realtime Tracker) was used. Which can also implement multi-object tracking.

* This algorithm assigns unique IDs to animals and tracks their movements over time.
* Metrics such as movement patterns, activity duration, and rest periods were extracted to maintain an activity map.
* Detected movements were classified into predefined behavior categories using a Convolutional Neural Network (CNN) trained on labeled behavioral data.

3. Anomaly Detection Using Machine Learning

The system employs autoencoders and one-class SVM (Support Vector Machine) for anomaly detection.

* Autoencoders: This model learns normal behavioral patterns by encoding and reconstructing activity data. Significant changes in reconstruction error indicate abnormal behavior.
* One-Class SVM: Applied for real-time anomaly detection by learning normal behavioral features and flagging unusual deviations.
* Implementation Steps:
  1. Feature extraction from tracked animal movement data.
  2. Training of autoencoders to reconstruct normal behaviors.
  3. Comparison of new data with learned patterns to detect anomalies.

4. Disease Detection and Health Monitoring

Thermal imaging data is processed using thresholding and region-based segmentation. This is used to detect signs of fever or inflammation.

* K-Means Clustering: Used to segment temperature regions on animals’ bodies.
* Gradient-Based Edge Detection: Helping in early disease detection by identifying abnormal temperature variations.

5. Alert Mechanism and Decision System

The alert system is based on Rule-Based Decision Tree. The notifications are triggered when specific conditions are met.

* If an animal exhibits abnormal behavior for a predefined time threshold, an alert is sent.
* If thermal readings exceed normal levels, a health warning is generated.
* If an unauthorized entity is detected, an intrusion alert is triggered.

This combination of deep learning, machine learning, and rule-based algorithms ensures accurate livestock monitoring.

***Experimental Setup and Testing***

Field testing is essential for evaluating the practical efficacy of the system in real-world conditions. The system was deployed on multiple farms with varying livestock types and environmental conditions to assess its detection accuracy and its performance in a real window. The behavior analysis capabilities were also put to test. The testing setup included real-time video cameras, IoT sensors for environmental monitoring, and mobile devices for alert notifications. Additionally, precision, recall, and F1score metrics were used to assess the system for classification performance.

Testing Methodology:

* Data Collection: Video feeds and sensor data were gathered from various locations to ensure diversity in environmental factors, and system adaptability.
* Performance Evaluation: Performance was assessed using both quantitative and qualitative methods. Visual inspection of system responses to unusual animal behavior and health changes were assessed.
* Real-World Validation: The system was evaluated in both small-scale and largescale farm settings. And was tested for its scalability and responsiveness in different contexts.

# results and discussion

The system achieved a detection accuracy of 94% for animal identification. Its ability to distinguish between livestock and intruders is effective. Behavior analysis, particularly in identifying abnormal activities such as restlessness, unusual grazing patterns, was high. There was an 87% precision rate for early disease prediction.

***Key Findings***

* RealTime Alerts: Automated alerts for abnormal behavior in livestock, health symptoms, and intrusions were delivered promptly. The system helped in reducing the need for constant supervision of the farm and allows for faster intervention.
* Behavioral Anomaly Detection: Machine learning algorithms helped for accurately identifying atypical behavior patterns. Predict illnesses like fever or injury were easily identified before clinical symptoms appeared.
* Improved Efficiency: The integration of IoT sensors enhanced the system’s ability to monitor environmental conditions, improving overall farm management efficiency by approximately 30% compared to manual methods.

These results showcase the potential for AI systems to improve livestock health monitoring and also enhance overall farm security and reduce labor cost.

***Challenges and Limitations***

Environmental Conditions:

* Poor lighting or extreme weather conditions such as fog or heavy rain affected the clarity of the video, making accurate animal identification and behavior analysis difficult. This limitation was particularly noticeable. Sensors were inaccurate in extreme weather conditions.

Large-Scale Dataset Requirements:

* Training accurate machine learning models, particularly for behavior recognition and anomaly detection, required large labeled datasets. The lack of sufficient labeled data for smaller farms was a key limitation, as it made it difficult to make model refinement and generalization across diverse livestock types.

Cost and Setup:

* While the AI-powered system is more cost-effective than some high-end solutions, the initial setup costs for the IoT sensors, thermal cameras, and computing infrastructure, may be troublesome for smaller-scale farmers. Additional infrastructure for cloud storage and data processing could further increase the investment required.

# conclusion

This research demonstrates the potential of AI in revolutionizing livestock monitoring. The system offers improved health surveillance, and better farm management efficiency. The proposed system provides a general solution for modernizing farms by combining real-time object detection, behavior tracking, anomaly detection, and IoT-based environmental monitoring. This research highlights the positive impact of AI-driven technologies in livestock monitoring. The ability of system to enhance farm management, monitoring animal health, and optimize security is highly efficient. System provides an automated approach to livestock monitoring by integrating real-time video analysis, behavior tracking, object detection, and anomaly detection.

The experimental results demonstrate the system’s effectiveness. The system shows high accuracy in animal identification, behavioral anomaly detection, and disease prediction. Automated alerts with significantly reduced response times allows for faster supervision. Additionally, the use of IoT sensors improved environmental monitoring, contributing to better decision-making in daily farm operations.

Despite its successes, the system encountered several challenges and limitations, including:

* Environmental factors affecting video clarity.
* The need for large-scale annotated datasets for improved model accuracy.
* The high initial cost of deployment.

Addressing these issues will require advancements in machine learning, better data acquisition methods, and cost-effective hardware solutions. This will solve the issues and make the system accessible to a broader range of farmers.

Looking forward, future enhancements will focus on integrating advanced deep learning models like RNNs for improved behavioral pattern recognition, implementing drone-based surveillance for larger farm areas, and using edge computing for real-time data processing with reduced latency. Also, increase the system’s ability to detect early signs of illness and improve livestock welfare.

In conclusion, this research sets the foundation for scalable, efficient, and intelligent farm management solutions by lowering the need for manual supervision while enhancing productivity, animal well-being, and security. By refining AI algorithms, expanding dataset availability, and reducing hardware costs, this system has the potential to completely transform modern farming practices. Livestock monitoring will be more proactive, data-driven, and accessible to farmers worldwide.

***Key Contributions Aligned with Research Objectives***

AI-Powered Animal Detection

* Objective: Develop an AI-powered system for farm animal classification and detection.
  + Contribution: Implements MobileNet SSD to accurately detect, classify, and differentiate between farm animals and potential intruders in farm, real-time.

Behavior Tracking & Anomaly Detection

* + Objective: Integrate behavior tracking algorithms to monitor normal and abnormal activities.
  + Contribution: Makes use of machine learning to analyze movement patterns, feeding habits, and social interactions, detecting deviations that may point to stress, aggression, or health issues.

Early Disease Prediction

* + Objective: Implement anomaly detection techniques for disease identification in an early stage.
  + Contribution: Integrates thermal imaging and AI-based analysis to detect fever, lethargy, and other symptoms of diseases, allowing proactive intervention.

Automated Alerts & Notifications

* + Objective: Improve farm security and monitoring by sending real-time alerts.
  + Contribution: Enables real-time notifications via SMS or email for intrusion detection, abnormal animal behavior, or potential diseases.

IoT-Enabled Monitoring

* + Objective: Utilize IoT-based environmental monitoring to enhance decision-making.
  + Contribution: Temperature, humidity, livestock conditions, additional insights beyond visual monitoring were tracked with use of sensors.

Comprehensive Data Storage & Analysis

* + Objective: Store historical data for trend analysis.
  + Contribution: Maintains structured records of animal behavior dataset, allowing predictive analytics and long-term health monitoring.

Enhanced Security Features

* + Objective: Distinguish between farm animals and intruders for farm security.
  + Contribution: The system identifies unauthorized movement and potential threats, helping prevent livestock theft and predator attacks.

Multi-Modal Data Integration

* + Objective: Enhance system accuracy using multiple data sources.
  + Contribution: Combines AI, IoT, and computer vision techniques to create a more reliable monitoring system.

Scalability & Smart Farming Integration

* + Objective: Make the system adaptable to various farm sizes and smart agriculture practices.
  + Contribution: Supports cloud storage, remote access, and smart device integration, making it applicable to both large and small farms.

Performance Evaluation & Benchmarking

* Objective: Compare the proposed system’s performance with existing monitoring techniques.
* Contribution: Demonstrates superior accuracy, efficiency, and cost-effectiveness compared to traditional manual observation methods.

***Future Enhancements***

This research will focus on enhancing the capabilities and scalability of the system to overcome current limitations.

Advanced Deep Learning Models:

* Implementing more sophisticated deep learning architectures for behavior analysis, such as recurrent neural networks (RNNs) or attention-based models, will improve the system’s ability to handle complex patterns and improve prediction accuracy. These models can improve early disease detection.

Drone Integration:

* Integrating drones equipped with cameras and thermal imaging sensors could expand the surveillance area, particularly in larger or remote farms. Drones would provide a more comprehensive view, helping to monitor livestock across vast areas more efficiently than stationary cameras.

Enhanced Disease Detection:

* To improve health monitoring, future versions of the system could incorporate biomarkers and more advanced imaging techniques, such as ultrasound or infrared spectroscopy, to detect diseases at even earlier stages. These advancements would allow for more accurate and timely diagnosis, minimizing the spread of illness but costlier.

Edge Computing:

* Implementing edge computing would enable real-time data processing onsite, reducing latency and dependency on internet connectivity, especially in rural areas with limited network access.

Future Work will focus on further refining the machine learning models. Integrating additional data sources and larger-scale deployments are part of it. The goal is to make this technology more accessible, cost-effective, and applicable to a broader range of agricultural operations, ultimately improving livestock care and farm productivity.

# REFERENCES

1. Li, X., et al. (2021). RFID-based Livestock Identification and Tracking for Real-time Monitoring. Journal of Agricultural Systems, 34(2), 234-245.
2. Patel, A., et al. (2022). IoT-Enabled Environmental Sensors for Livestock Monitoring: A Comparative Study. Agricultural Engineering Review, 48(1), 112-124.
3. Wang, Y., et al. (2020). Computer Vision Techniques for Behavior Recognition in Livestock. Journal of Computer Vision, 58(3), 213-229.
4. Smith, R., et al. (2023). Utilizing Thermal Imaging for Early Detection of Livestock Health Issues. Veterinary Diagnostics, 26(4), 321-335.
5. Yousefi, H., et al. (2023). Deep Learning Approaches for Anomaly Detection in Animal Movements. International Journal of Machine Learning in Agriculture, 19(2), 75-88.
6. Jones, D., et al. (2024). Hybrid AI-IoT System for Real-time Livestock Behavior Tracking: A Case Study. Journal of Smart Agriculture, 35(1), 45-58.
7. Kim, J., et al. (2023). Drone-based Surveillance for Livestock Monitoring: Advancements and Challenges. International Journal of Agricultural Robotics, 14(3), 98-110.
8. Ahmed, Z., et al. (2021). Advances in AI for Precision Livestock Farming: A Review. Computers in Agriculture, 22(2), 145-160.
9. Zhang, H., et al. (2022). Predictive Modeling for Livestock Health Using AI and IoT Sensors. Journal of Agricultural Informatics, 38(4), 103-115.
10. Muthukumar, S., et al. (2020). Real-time Monitoring and Anomaly Detection for Cattle Health Using AI and IoT. Agricultural Technology, 19(1), 85-99.
11. Liu, J., et al. (2021). AI-Driven Disease Prediction for Livestock Based on Movement and Behavior Patterns. Journal of Livestock Science, 42(2), 195-209.
12. Choi, D., et al. (2023). AI in Livestock Surveillance: Real-time Animal Detection and Threat Mitigation. Security and Agriculture Journal, 26(1), 70-85.
13. Khan, A., et al. (2022). Development of Smart Farms Using AI and Internet of Things (IoT) Technologies. International Journal of Smart Systems, 12(2), 134-148.
14. Liu, Y., et al. (2022). Use of Computer Vision and Machine Learning for Livestock Behavior and Disease Monitoring. Veterinary Informatics, 31(3), 221-233.
15. Turner, M., et al. (2023). AI and Thermal Imaging Integration for Early Detection of Livestock Diseases. Precision Agriculture, 45(4), 308-320.
16. Sharma, R., et al. (2021). Integrating IoT with AI for Enhanced Farm Security and Livestock Protection. Journal of Agri-Tech, 29(1), 61-74.
17. Singh, K., et al. (2020). Automated Anomaly Detection in Animal Behavior Using Machine Learning Algorithms. Journal of Agricultural Robotics, 18(2), 52-64.
18. Jha, S., et al. (2022). Machine Learning Techniques for Disease Diagnosis in Livestock. Animal Health Informatics Journal, 28(4), 145-158.