# Development of a UAV-Acquired Dataset for Machine Learning-Based Farm Intrusion Detection

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## Abstract

While Unmanned Aerial Vehicles (UAVs) offer promising capabilities for aerial monitoring, there remains a critical shortage of publicly available, UAV-acquired datasets specifically designed for machine learning-based intrusion detection in agricultural settings. Existing datasets either lack aerial perspectives, omit essential "empty space" categories for negative sampling, or are not optimized for ternary classification tasks required for robust farm security systems. To bridge this gap, this paper introduces a novel UAV-acquired dataset specifically designed for farm intrusion detection. Collected through systematic aerial surveillance supplemented with ground-level captures, the dataset comprises 2,067 images across three essential categories: animals (907 images), people (588 images), and empty spaces (572 images). The inclusion of empty spaces enables models to distinguish between normal and intrusion scenarios, while UAV-captured aerial views provide comprehensive coverage ideal for large-scale farm monitoring. We detail the data collection methodology using consumer-grade UAVs, preprocessing techniques, and dataset characteristics, with visualizations confirming its balanced distribution and suitability for real-world applications. To demonstrate practical utility, We provide an initial baseline model which achieves a 98.4% accuracy and full documentation to facilitate reuse and extension by the community. The dataset and related codes are publicly available at https://github.com/mugishastanley/Intrusion_detection to support further research in UAV-based agricultural security and represents a significant contribution toward automated intrusion detection systems in the era of Agriculture 4.0.

**Keywords:** Unmanned Aerial Vehicles (UAVs), farm intrusion detection, machine learning, dataset creation, livestock security, image processing.

## 1. Introduction

Livestock farming is a vital component of global agriculture, providing essential meat and dairy products that support food security and economic stability in many regions. However, livestock farms often span vast areas, making constant manual monitoring challenging and resource-intensive. Intrusions, such as theft by unauthorized individuals or disruptions caused by stray animals, result in substantial financial losses and operational disruptions. For instance, recent statistics indicate that livestock theft has a severe economic impact, with South Africa alone reporting losses exceeding R7 billion over the past five years due to the theft of cattle, sheep, and goats (clack et al. 2025). Globally, the economic burden of livestock theft and intrusions is estimated to be in the billions of dollars annually, affecting farmers' livelihoods and the broader agricultural supply chain (lombard 2025). Traditional security measures, such as physical fencing, human patrols, or basic camera systems, are often inadequate for large-scale operations due to their high costs, limited coverage, and vulnerability to environmental factors. These methods also fail to provide real-time alerts or automated responses, leaving farms exposed to risks during off-hours or in remote areas.

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, offer a transformative solution by enabling aerial surveillance over wide-open spaces.Automated UAV-based monitoring offers a scalable, non-intrusive, and cost-efficient solution. UAVs can provide real-time, high-resolution imagery from elevated perspectives, allowing for the detection of intruders in remote or hard-to-reach areas without requiring constant human presence. This technology is particularly advantageous in livestock farms, where animals graze over large pastures, and intrusions can occur at any time, including under varying environmental conditions like different lighting or weather. However, the lack of a standardized, open benchmark dataset for farm intrusion detection is a critical gap.

To address the above challenges, we propose an automated intrusion detection system using machine learning (ML) models trained on visual data acquired primarily via UAVs. The system classifies images into three categories: ``animals'' (representing farm livestock such as goats and cows), ``people'' (potential intruders or thieves), and ``empty spaces'' (indicating no intrusion). This ternary classification enables real-time alerts to farmers, mitigating risks effectively and reducing reliance on manual intervention. The integration of UAVs ensures comprehensive coverage, minimizing blind spots and enhancing detection accuracy in dynamic farm environments.

This paper details the creation of a dedicated dataset for this purpose, developed at Soriti University. We outline the problem's significance, data collection methods with a focus on UAV deployment, dataset characteristics, visual analyses, and comparisons with existing datasets. By making the dataset publicly accessible, we aim to contribute to the growing field of smart agriculture, particularly through UAV-enabled technologies that promote sustainable and secure farming practices.

## 2. Literature Review

The integration of Unmanned Aerial Vehicles (UAVs), computer vision, and machine learning in agricultural security has gained significant traction in the era of Agriculture 4.0. While these technologies enable advanced monitoring and data-driven decision-making, a critical analysis reveals substantial limitations in existing approaches specifically for farm intrusion detection. This review systematically examines current literature to identify persistent gaps that our work addresses.


IJBEST ISSN (2959-586X) and ISBN (978-9970-9943-4-2)

**Table 1:** Comparative analysis of UAV-Based monitoring systems in agriculture, compares this work with key existing UAV datasets, clarifying the unique contribution of our dataset

| Study | Dataset Name | Primary Focus | Models | Limitations |
|---|---|---|---|---|
| **Gao et al. (2024)** | Custom (VisDrone + Roboflow augmentation) | Livestock classification & object detection | YOLOv7, Faster R-CNN, SSD, Mask R-CNN | Focuses on classification only; no intrusion-specific dataset |
| **Doll & Loos (2024)** | SheepCounter Dataset | Sheep monitoring in UAV images | YOLOv5-v8, SSD, EfficientDet | Species-specific (sheep only); no human intruders |
| **Mou et al. (2023)** | WAID Dataset | Wildlife detection & conservation | SE-YOLO (YOLOv7 with self-attention) | Wildlife focus; no empty space class; conservation-oriented |
| **Touray & Jadama (2024)** | Custom augmented dataset | Farm intrusion detection | InceptionV3 with data augmentation | Simulated conditions; limited real-world UAV data |
| **Nong & Aziz (2024)** | Various agricultural datasets | Crop health, intrusion, livestock monitoring | EfficientNet, various DL models | Broad survey; no dedicated intrusion dataset |
| **Kuru et al. (2023)** | Airborne vision-based datasets | Livestock monitoring with thermal imagery | Various AI approaches | Focus on livestock counting/health |
| **Zhao et al. (2025)** | UAV-LiDAR Cattle Dataset | Cattle growth monitoring | 3D point cloud analysis | Growth monitoring focus; no intrusion detection |


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| Study | Dataset Name | Primary Focus | Models | Limitations |
|---|---|---|---|---|
| **Antonakakis et al. (2024)** | SheepCounter, Sheep Detection from Above | Edge computing for livestock | TPH-YOLOv5 | Species-specific; edge computing focus |
| **González-Rodriguez et al. (2024)** | Farm-Flow Dataset | Network intrusion detection | Various ML models | Network-based (not vision-based) |
| **Aliane (2025)** | Various wildlife datasets | Wildlife monitoring & anti-poaching | YOLO, Mask R-CNN | Wildlife conservation focus |
| **Rajesh et al. (2024)** | Multiple object detection datasets | Real-time animal intrusion | YOLOv8 with IoT integration | Crop protection focus; limited livestock security |
| **Roboflow Farm Dataset (2023)** | Farm Intrusion Detection Dataset | Object detection for farm security | Various object detectors | No empty space class; limited UAV emphasis |
| **Our Work (2025)** | **UAV-Acquired Farm Intrusion Dataset** | **Farm intrusion detection with ternary classification** | **MobilnetV3 and CNN (benchmarked)** | **Specific to Ugandan farm conditions** |

### 2.1 Current State of UAV-Based Agricultural Monitoring

Recent years have witnessed considerable advances in UAV applications for agriculture. Gao et al. (2024) demonstrated impressive performance with mAP scores up to 97.6% for livestock classification using augmented datasets from VisDrone and Roboflow. Similarly, Mou et al. (2023) achieved remarkable accuracy (mAP: 0.983) with their WAID dataset for wildlife detection using enhanced YOLOv7 models. However, these studies exhibit a critical limitation: their focus remains predominantly on wildlife conservation or general livestock monitoring rather than targeted intrusion detection for farm security.

The specialization trend continues in works like Doll and Loos (2024), who provided valuable insights into sheep monitoring but restricted their analysis to single-species applications. This narrow focus significantly limits practical deployment in diverse farming environments where multiple animal types coexist. Similarly, Zhao et al. (2025) introduced sophisticated UAV-LiDAR systems for cattle growth monitoring, representing technical advancement in 3D data analysis but overlooking the pressing



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security concerns that affect farmer livelihoods daily.

### 2.2 The Intrusion Detection Paradigm Critical Gaps

Several studies have explicitly addressed intrusion detection but with notable limitations. Touray and Jadama (2024) developed machine learning models for farm intrusions using InceptionV3, yet their reliance on simulated nighttime conditions and limited real-world UAV data raises questions about practical applicability. Their approach, while methodologically sound, fails to leverage the comprehensive perspective that UAV aerial surveillance provides.

Rajesh et al. (2024) achieved impressive results (>99% accuracy) with YOLOv8 for animal intrusion detection, demonstrating the potential of modern architectures. However, their focus on crop protection from wildlife diverges from the specific challenges of livestock security, where human intruders pose equal or greater economic threats.

Perhaps most telling is the analysis of existing datasets. The widely used Roboflow Farm Intrusion Detection Dataset includes classes for "Goat, Cow, Person, and no_mask" but conspicuously lacks an "empty space" category essential for reducing false positives in real-world deployment. Similarly, the Sheep Counter and Sheep Detection from Above datasets (Antonakakis et al., 2024), while valuable for specific applications, remain species-specific and omit human intruders entirely a critical oversight given that human theft constitutes a primary economic threat to farmers.

### 2.3 Methodological and conceptual limitations

The literature reveals several methodological shortcomings. Kuru et al. (2023) presented comprehensive airborne vision-based datasets but emphasized thermal imagery and large-scale operations that may not be feasible for typical farming contexts. González-Rodriguez et al. (2024) introduced the Farm-Flow dataset with over one million instances for network-based intrusion detection, representing an important contribution to cybersecurity but leaving physical security unaddressed.

A pervasive issue across existing works is the lack of UAV-specific perspective optimization. While many studies utilize UAV-captured imagery, few explicitly design their datasets and methodologies around the unique advantages and challenges of aerial surveillance. This results in models that may perform well on benchmark datasets but underperform in practical farm settings where occlusion, varying altitudes, and lighting conditions present significant challenges.

### 2.4 Our Contribution

Our work directly addresses these identified limitations through several key innovations:

First, we introduce the first UAV-acquired dataset specifically designed for ternary classification in farm intrusion detection, including the crucial "empty space" category that enables robust negative sampling and reduces false alarms a feature conspicuously absent in existing datasets.

Second, unlike species-specific approaches (Doll & Loos, 2024; Zhao et al., 2025), our dataset encompasses multiple animal types and human intruders, reflecting the reality of diverse farming


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operations in developing regions.

Third, we optimize our data collection specifically for UAV deployment, capturing the unique aerial perspectives essential for comprehensive farm monitoring. This contrasts with datasets that merely include UAV imagery as one of multiple data sources without optimizing for aerial surveillance advantages.

Fourth, while existing works often focus on either wildlife conservation (Mou et al., 2023) or livestock management (Gao et al., 2024), we specifically target the economic security concerns of farmers, addressing the billion-dollar global problem of livestock theft and intrusion.

Finally, our dataset is explicitly designed for practical deployment in resource-constrained environments, with optimized image sizing for computational efficiency while maintaining the resolution necessary for accurate detection a consideration often overlooked in pursuit of maximal accuracy without regard to practical constraints.

The comparative landscape (summarized in Table 1) clearly demonstrates that while individual studies have advanced specific aspects of agricultural monitoring, none have provided a comprehensive solution for UAV-based farm intrusion detection. Our work fills this critical gap by providing a specialized, publicly available dataset that enables the development of robust intrusion detection systems specifically optimized for aerial farm surveillance in the developing world context.

## 2. Methods.

### 2.1. Problem Formulation

The primary objective is to detect intrusions on livestock farms by classifying visual inputs into three categories: (i) farm animals (e.g., goats, cows), (ii) people (potential thieves), and (iii) empty spaces (no activity). The "empty space" class serves as a negative sample to help models distinguish between normal (no intrusion) and abnormal (intrusion) scenarios. This improves model robustness and reduces false alarms. UAVs play a pivotal role by offering aerial views that capture broad farm layouts, enabling the identification of distant or hidden intruders effectively. This classification supports proactive security measures, such as automated alerts, in expansive farm settings.

### 2.2. Equipment and Data Collection

Data collection employed two complementary approaches, with UAVs as the central tool for achieving comprehensive aerial coverage. The UAV used was a consumer-grade quadcopter drone a dji Mavic3 Cine capable of 4K video recording. Flights were conducted in farm-like environments simulating livestock areas, capturing footage of people as potential intruders. To ensure dataset robustness, flights occurred at varying altitudes (5-20 meters), times of day (morning, afternoon, evening), and angles, accounting for diverse lighting conditions (e.g., bright sunlight, shadows) and environmental factors like wind and terrain. This resulted in bird's-eye views ideal for monitoring large grazing pastures where ground-level detection might fail due to occlusions.

Complementing the UAV data, mobile smartphones with 4K recording capabilities captured ground-level videos of animals primarily goats and some cows and empty farm spaces. These provided detailed, close-range perspectives to enhance texture and context recognition in the dataset. Videos from both sources were processed using online frame extraction tools. We used FFmpeg-based apps and mobile applications to generate individual images. From an initial pool of thousands of frames, we manually selected the clearest and most representative samples, prioritizing diversity in poses, lighting, and backgrounds to ensure the dataset's applicability to real-world intrusion scenarios.

**2.3. Data Processing and Resizing**

The original images, extracted from 4K videos, were high-resolution, leading to a dataset size of 4.87 GB. To optimize for machine learning training reducing computational load while preserving essential features, we resized all images to 255x255 pixels using a Python script. This process utilized the OpenCV library for efficient image manipulation. The resizing script iterated through the dataset folders, applying bilinear interpolation to maintain image quality.

This resizing reduced the dataset size to 99.5 MB, making it more manageable for training on standard hardware. All images are in JPEG format, each representing a single video frame, with sufficient resolution retained for distinguishing classes based on shapes, textures, and colors.

The processed dataset is organized into three folders:

1. Animals: 907 images of livestock, primarily goats and cows in various poses.
2. People: 588 images, mainly from UAV footage, depicting humans in farm-like settings.
3. Empty Spaces: 572 images of unoccupied farm areas, showing grass, fences, or soil.

This distribution reflects real-world farm scenarios, where animal presence is more frequent.

**2.4. Dataset Analysis and Visualization**

The final dataset comprises 2,067 images, with animals accounting for approximately 44\% (907 images), people 28% (588 images), and empty spaces 28\% (572 images) as shown in table 2. The slight imbalance favors animals, aligning with livestock farm priorities, but techniques like data augmentation can address this during model training. UAV-acquired images particularly enhance the people class by providing top-down views that simulate surveillance scenarios.

**Table 2:** Summary of the class distribution:

| **Categories** | **Number of Images** | **Percentage** |
|---|---|---|
| Animals | 907 | 44 |
| People | 588 | 28 |
| Empty Spaces | 572 | 28 |
| **Total** | 2067 | 100 |

Visualizations further illustrate the dataset's characteristics:
- Bar Graph and Pie Chart: The bar graph displays image counts per class, highlighting the dominance of the animals class. The pie chart provides a proportional view, confirming the approximate 44:28:28 split, which is suitable for farm-centric detection where UAV perspectives are critical for identifying


IJBEST ISSN (2959-586X) and ISBN (978-9970-9943-4-2)

sparse intrusions.

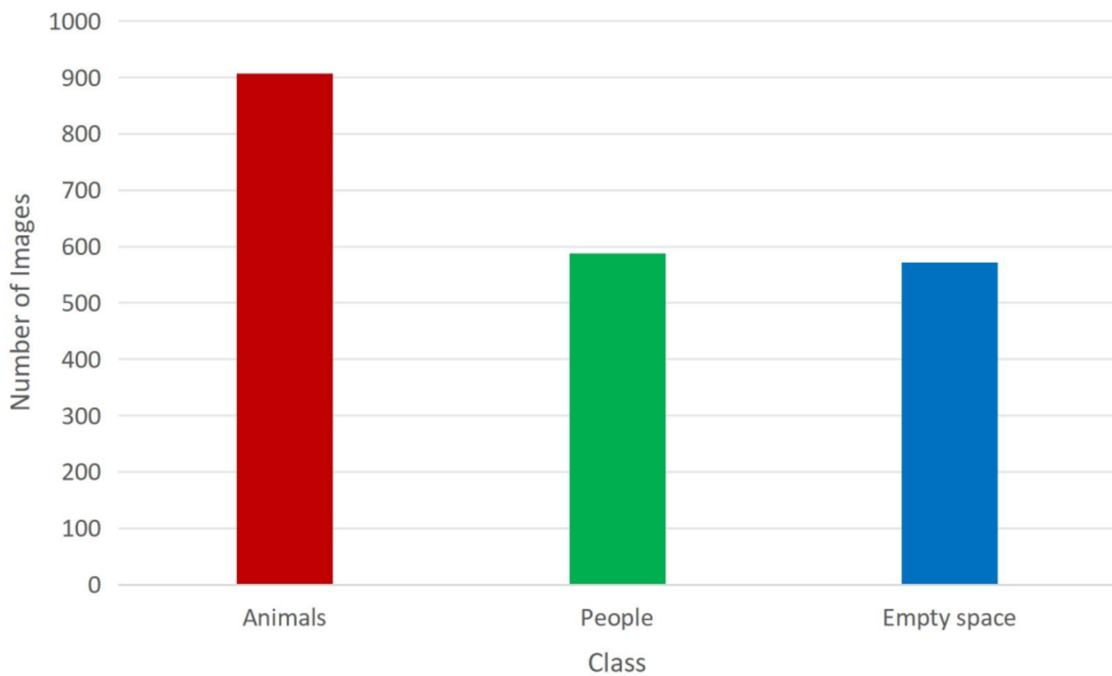

Figure 1 : A visual description of Data distribution.

## 3. Results

### 3.1 Additional Baseline Experiments.

We evaluated two widely used image classification models. A conventional Convolutional Neural Network (CNN) and MobileNetV3 to establish performance references for simpler architectures. The dataset was split into train, validation, and test subsets. Both models achieved meaningful performance in detecting intrusion events, establishing a benchmark for future research. A custom CNN with three convolutional layers, ReLU activations, max-pooling, and two fully connected layers. The model was trained from scratch using the same train/validation/test splits. The MobileNetV3 (Small variant), pre-trained on ImageNet and fine-tuned on our dataset, demonstrated significantly better performance while maintaining computational efficiency.

Table 3 shows that while the CNN baseline already performs strongly, MobileNetV3 Small with transfer learning improves across nearly all metrics, especially in precision and AUC, making it the stronger candidate for lightweight deployment. The mobilenet both accruare and efficient in resource consumption with fewer parameters and file size, thanks to its efficient design. In addition, Figure 2 shows that the mobilenet achieves a higher validation and train accuracy. These experiments provide insight into the difficulty of the dataset and highlight trade-offs between accuracy and efficiency. The comparative results indicate that while simple CNN architectures provide a low-complexity baseline, modern lightweight networks like MobileNetV3 offer superior trade-offs in terms of accuracy,



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efficiency, and generalizability. These findings reinforce the value of the dataset as a benchmarking resource for both traditional and lightweight deep learning models.

**Table 3**. Performance comparison of CNN and MobileNetV3 baselines on the UAV intrusion dataset

| Model | Precision | Recall | F1-score | AUC | Accuracy(%) | Size(MB) | Params (Million) |
|---|---|---|---|---|---|---|---|
| **CNN Baseline** | 0.967 | 0.969 | 0.968 | 0.993 | 96.77 | 12.61 | 3.31 |
| **MobileNetV3 small** | 0.988 | 0.983 | 0.985 | 0.999 | 98.38 | 3.87 | 1.01 |

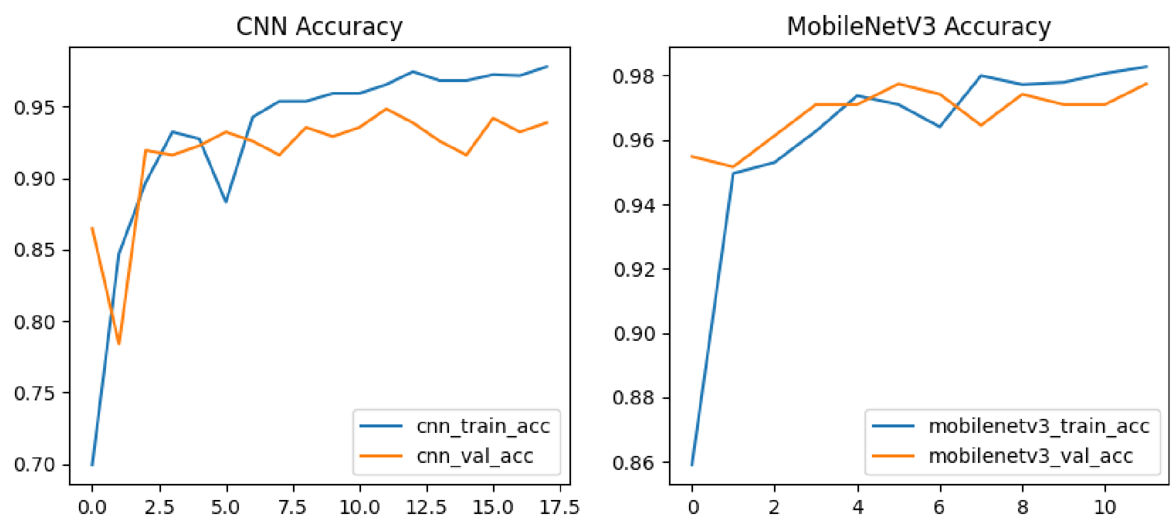


**Figure 2:** Train and validation accuracy for the baseline models.

### 3.2 Ethics and Privacy Considerations

Ethical considerations were paramount, particularly privacy in UAV footage. All images were anonymized to avoid identifiable features, and data collection complied with local regulations to minimize wildlife disturbance. The resized format ensures computational efficiency for resource-limited settings, but retaining original high-resolution images allows for advanced applications like super-resolution or transformer-based models. dataset release. In addition, human faces, vehicle plates, and personally identifiable features were blurred or excluded. Data collection was conducted with explicit landowner permissions, and no personal identifiers were included in annotations. This ensures compliance with privacy best practices for UAV-based data collection. In addition, we removed high-resolution captures of identifiable faces and license plates. When such elements were captured unintentionally, we either blurred them or excluded the image from the public release.

## 4. Discussion

Our UAV-centric dataset provides a practical and innovative resource for developing ML-based intrusion detection systems in livestock farming, effectively addressing physical intrusions through aerial surveillance. UAVs offer key advantages, including cost-effectiveness, scalability, and reduced human risk, as demonstrated in related studies on wildlife and livestock monitoring. Unlike existing datasets,


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ours combines human and animal intrusion scenarios in a reproducible, well-documented format. Baseline experiments confirm its suitability for training modern deep learning models. However, limitations exist. The dataset focuses on specific animals (goats and cows) and environments similar to Ugandan farms, which may require augmentation for broader applicability, such as different climates or livestock types. Class imbalance, while realistic, could bias models toward animal detection; techniques like oversampling or weighted loss functions can mitigate this. Comparisons with datasets like WAID and Roboflow highlight our unique contributions, such as the inclusion of empty spaces for negative sampling and UAV-specific perspectives.

Challenges in data collection included weather variability affecting UAV flights and ensuring image clarity from videos. Future enhancements could involve multi-sensor fusion (e.g., thermal imaging) for nighttime detection.

## 5. Potential Applications and Future Work

The dataset has broad applications in smart agriculture. It can train models for real-time UAV-based surveillance systems that send alerts via SMS or apps upon detecting people or stray animals. Integration with IoT devices could enable automated responses, like activating lights or sirens.

Future work includes expanding the dataset with more diverse scenarios, such as nighttime or adverse weather captures, and adding annotations for object detection (e.g., bounding boxes). We plan to conduct experiments evaluating ML models like YOLO and CNNs on this dataset, benchmarking against baselines. Collaboration with farmers for field trials will validate real-world performance, potentially leading to open-source IDS tools.

Additionally, exploring hybrid systems combining our vision dataset with network-based ones like Farm-Flow could provide comprehensive security against both physical and cyber threats.

## 6. Conclusion

This paper introduces a novel UAV-acquired dataset for farm intrusion detection, collected through innovative aerial methods and optimized for ML applications. By categorizing 2,067 images into animals, people, and empty spaces, it enables automated systems to safeguard livestock farms effectively. We provide baseline models based on a CNN and mobilenet for benchmarking and each one achieves a high accuracy of 96.8 and 98.4% respectively. The emphasis on UAV technology advances smart agriculture, offering a robust foundation for future innovations in AI-driven, drone-based security solutions.

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IJBEST ISSN (2959-586X) and ISBN (978-9970-9943-4-2)