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Recent Trends and Challenges in Animal Intrusion Detection and Repellent Systems

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ABSTRACT

The increasing frequency of animal intrusions into human-inhabited or agri- cultural areas has emphasized the need for efficient detection and repellent systems to mitigate human-wildlife conflict. This paper examines advancements in technologies such as Passive Infrared sensors, Convolutional Neural Networks, and IoT-based frameworks that form the foundation of modern animal intru- sion management systems. PIR sensors are explored for their effectiveness in motion detection, while CNNs enable accurate species identification, crucial for activating targeted responses. Deterrent mechanisms, including ultrasonic frequency modulation and light-based systems, are analyzed for their ability to repel animals humanely and species-specifically.

Additionally, the work highlights IoT-integrated systems that facilitate real-time alerts and communication with administrators, enhancing response efficiency. Case studies on CNN-based animal detection, IoT-enabled agricultural protection systems, and ultrasonic repellent solutions underscore the potential of combin- ing hardware and AI technologies. The evaluation focuses on detection accuracy, scalability, adaptability to diverse environments, and responsiveness. By consoli- dating insights from these methodologies, the work identifies trends in sustainable and humane animal intrusion management systems for applications in agriculture, wildlife conservation, and public safety.

This analysis underscores the transformative role of AI and IoT in addressing the challenges of coexistence with wildlife, paving the way for scalable and ethical solutions to mitigate conflicts.

Keywords: Animal intrusion, PIR sensors, CNN, Ultrasonic deterrents, IoT, Deep learning, Wildlife management

1. Introduction

Human-wildlife conflict represents a persistent challenge across the globe, particularly in regions where human activities overlap with natural animal habitats. These conflicts often lead to crop damage, threats to public safety, and significant economic losses. Traditional mitigation measures such as physical barriers, manual monitoring, and chemical repellents have been employed, but these approaches frequently lack scala- bility, efficiency, and sustainability. In response, advancements in artificial intelligence

, the Internet of Things , and deep learning have enabled the development of innova- tive, automated systems for managing animal intrusions in a humane and sustainable manner.

The increasing threat of animal intrusion in agricultural and industrial environ- ments has driven significant advancements in animal detection and repellent systems. These systems are crucial for preventing the damage caused by wild animals, such as rodents, boars, and other species, which can negatively impact crops, infrastructure, and public safety. At the heart of these innovations are the developments in detec- tion technologies and deterrent mechanisms, which have transitioned from basic sensor systems to more advanced, data-driven approaches that integrate machine learning and artificial intelligence (AI) techniques [1, 2, 5]. The ability to ccurately detect animal intrusion in real-time and deploy appropriate countermeasures, such as ultra- sonic repellents or alarms, has become essential for applications in agriculture, wildlife conservation, and industrial settings [3, 6, 7].

Traditional animal intrusion detection systems heavily relied on hardware-intensive methods such as infrared sensors or motion detectors. These systems were effective in controlled environments but struggled to adapt to the challenges of dynamic and outdoor settings, where factors such as weather, lighting, and animal behavior varia- tions come into play [5, 8]. As applications expanded, there was a shift towards more sophisticated, data-driven approaches that utilized machine learning to handle these challenges more effectively. Researchers began developing systems capable of contin- uously learning from environmental data and adjusting detection models to optimize performance under varying conditions [2, 6].

The advent of deep learning and computer vision has significantly enhanced the capabilities of animal detection systems. Models such as convolutional neural networks (CNNs) and object detection algorithms have proven effective in identifying and clas- sifying animals from real-time video streams and sensor data [9, 10]. These systems are capable of accurately distinguishing between various species, providing valuable insights into intrusion events and enabling the deployment of targeted deterrents, such as ultrasonic sound waves or alarms, that are tailored to specific animal species [4, 11, 12].

Recent research has focused on further improving the efficiency and accuracy of animal detection systems by integrating deep learning with IoT technologies. Bal- akrishnan et al. (2021) explored the application of IoT devices in animal intrusion detection, leveraging real-time data from sensors and cameras to provide continuous monitoring and automatic responses [7]. This IoT integration enables scalable systems that can be deployed across large agricultural areas, offering real-time monitoring and timely interventions to prevent damage.

In the area of animal repellent systems, ultrasonic frequencies have become a popu- lar solution, particularly for rodents and small mammals. Wal et al. (2024) developed a variable frequency generator for ultrasonic repellent, which allows farmers to customize the frequency range depending on the specific type of animal and the environment [1]. This innovation marks a shift towards more adaptable and efficient repellent solutions. Additionally, advances in machine learning algorithms have enabled more precise classification of animal species. Ibraheam et al. (2020) implemented deep learning models for species recognition, allowing for real-time classification of animals based on sensor data, which helps in identifying specific intruders and applying appropriate countermeasures [5]. This capability is crucial for minimizing crop damage by enabling the detection of particular animal species that may pose a higher threat to agriculture. Several studies have also explored hybrid models that combine different AI tech- niques to improve animal detection systems. For instance, Ravoor et al. (2020) designed a deep learning-based animal intrusion detection system that integrates mul- tiple models to enhance detection accuracy and response speed, even in dynamic environments [6]. These hybrid models can provide more robust solutions for managing animal intrusion across various agricultural and industrial settings.

The use of object detection algorithms, such as YOLO , has proven particularly effective in real-time animal detection. Kathir et al. (2024) utilized YOLOv8 for animal intrusion detection, demonstrating its ability to accurately track and classify animals in agricultural fields [10]. This method has become a critical component in modern animal intrusion detection systems, providing rapid identification and response to intrusions.

Moreover, advances in hybrid deep learning approaches for animal detection, as demonstrated by Thomas et al. (2023), have contributed to the development of systems that can detect animals in complex and diverse environments, such as farms and forests, by combining different deep learning models for improved performance [13]. These systems provide scalable and flexible solutions for preventing damage caused by animal intrusion.

Prasad (2023) developed an intelligent animal repellent system that uses deep learning to detect and classify animals in real-time, triggering appropriate repellent mechanisms when necessary [14]. This system integrates both detection and repellent functions, offering a comprehensive solution for protecting crops and infrastructure from animal threats.

In the context of sustainable agriculture, Gupta et al. (2022) introduced a wildlife intrusion detection system that integrates deep learning and AI to help mitigate the impact of animal threats on farming practices [16]. This work emphasizes the impor- tance of using advanced technologies to safeguard agricultural lands while promoting environmental sustainability.

Finally, Sharma et al. (2021) focused on using convolutional neural networks (CNNs) for animal detection in agricultural fields, providing a reliable method for protecting crops from unwanted animal intrusions [17]. Their work showcases the ongoing advancements in animal detection technology, which continues to evolve to meet the growing challenges posed by animal threats in agricultural and industrial environments.

In conclusion, this study focuses on addressing key challenges in animal intru- sion detection by exploring advanced AI-driven methodologies and IoT-integrated frameworks. By emphasizing real-time processing, adaptive repellent mechanisms, and improved accuracy across diverse environmental conditions, the research contributes to the development of more efficient and humane solutions. The integration of hybrid detection systems and adaptive technologies offers innovative approaches to enhance performance and ensure scalability, paving the way for sustainable and ethical animal intrusion management strategies in various contexts.

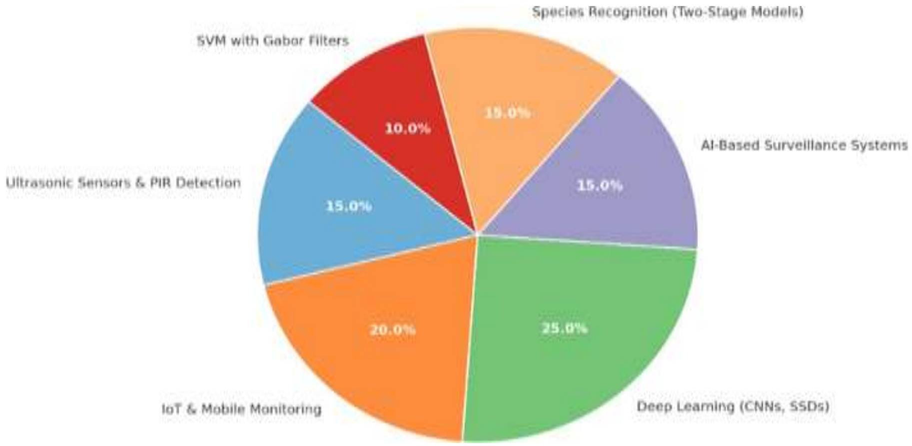

Fig. 1: Key Limitations of Existing Systems.

Figure 1, illustrates the distribution of various technologies used for animal iden- tification in animal intrusion detection and repellent systems. The largest segment, approximately 25%, is attributed to ”Deep Learning (CNNs, SSDs),” highlighting its dominance in modern animal detection approaches. ”IoT Mobile Monitoring” accounts for 20%, reflecting the integration of interconnected devices in such systems. ”Ultrasonic Sensors PIR Detection,” ”AI-Based Surveillance Systems,” and ”Species Recognition (Two-Stage Models)” each contribute 15%, showcasing the diversity of methods employed. Finally, ”SVM with Gabor Filters” represents a smaller share of 10%, emphasizing the role of traditional machine learning techniques. This distribution underscores the multifaceted nature of animal detection and repellent technologies.

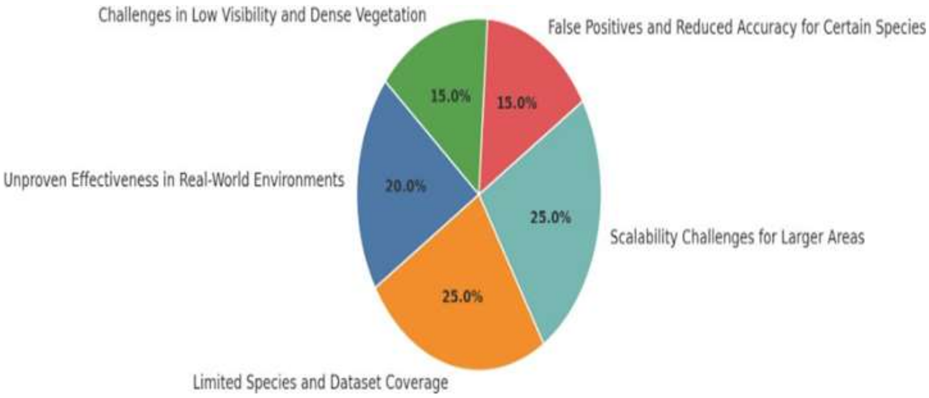

Fig. 2: Algorithms and methodologies adapted by existing system.

Figure 2, highlights the key limitations of animal detection systems. The largest challenges, each representing 25%, are scalability for larger areas and limited species/- dataset coverage. Unproven effectiveness in real-world environments accounts for 20% of the limitations. Challenges in low visibility and dense vegetation, as well as false positives and reduced accuracy for certain species, each represent 15%. These factors collectively outline areas requiring improvement for better system performance.

1.1 Problem Statement

Mitigating human-wildlife conflict presents significant challenges due to the complex- ity and unpredictability of animal behavior, as well as the diverse environmental conditions in which these conflicts occur. Traditional methods, such as physical barri- ers, manual monitoring, and chemical repellents, often fail to provide comprehensive and sustainable solutions, being limited by their inability to adapt to varying species, terrains, and circumstances. Existing technological systems, including basic motion sensors and non-specific deterrents, suffer from high false-positive rates, limited scal- ability, and lack real-time identification capabilities. While deep learning models offer improved detection accuracy, they require substantial computational resources and are heavily reliant on high-quality training datasets, reducing their effectiveness in real- world, resource-constrained settings. These limitations underscore the urgent need for an adaptive, efficient system that integrates advanced detection, identification, and deterrent technologies to address the specific challenges of animal intrusion in diverse environments, while ensuring humane and sustainable conflict mitigation practices.

1.2 Motivation

The increasing interactions between human activities and wildlife in agriculture, con- servation areas, and urban settings highlight the need for automated systems to manage animal intrusions effectively. Existing methods, including manual monitor- ing, physical barriers, and chemical repellents, often fail to adapt to the dynamic and unpredictable nature of animal behavior, leading to inefficiencies and potential harm to both humans and wildlife. Furthermore, the inability of these systems to provide real-time detection, species-specific identification, and tailored deterrent mechanisms limits their effectiveness in preventing conflicts and protecting critical areas.

Recent advancements in IoT, AI, and deep learning technologies present a com- pelling opportunity to address these challenges. The integration of intelligent detection systems, adaptive repellents, and automated alert frameworks has the potential to enhance scalability, accuracy, and humane conflict management. By leveraging these advancements, it becomes possible to develop solutions that not only mitigate human- wildlife conflicts but also promote coexistence and sustainability. This motivates the creation of innovative, adaptive systems capable of operating in diverse environmental conditions, meeting the needs of modern agriculture, wildlife conservation, and public safety.

The following are the contributions of the paper:

- To evaluate the effectiveness of PIR sensors and IoT-based detection mechanisms in handling diverse environmental conditions and dynamic animal movements.
- To explore and implement advanced recognition architectures, such as CNNs, for accurate species identification, even in challenging scenarios with overlapping or obscured visual data.
- To identify key limitations in existing animal intrusion detection and management systems, including high false-positive rates, limited scalability, and lack of real-time alert mechanisms, and propose innovative solutions to address these challenges.

- To benchmark the developed system against existing methodologies using simulated and real-world test environments, highlighting its accuracy, scalability, and responsiveness.
- To explore practical applications of the proposed system in fields such as agriculture, wildlife conservation, and public safety, ensuring humane and sustainable conflict mitigation strategies.

The remainder of this paper is organized as follows: Section 2 provides a compre- hensive literature review, highlighting key developments and limitations in existing animal intrusion detection and repellent systems, including traditional methods, sensor-based approaches, and machine learning architectures. Section 3 details the methodologies adopted for the system, emphasizing the innovative integration of sensor networks, and advanced detection algorithms. The implementation details of various methodologies are covered in Section 4. The evaluation results are presented and analyzed in Section **??**, comparing the system's performance against state-of- the-art techniques on standard benchmarks. Finally, Section 5 concludes the paper by summarizing findings and suggesting potential directions for future research.

2. Related Works

The Variable Ultrasonic Frequency Generator is an eco-friendly device to repel rodents using 20–125 kHz ultrasonic waves triggered by a PIR sensor. Controlled by an Arduino Nano, it costs 20–25 and avoids harmful chemicals. Lab tests showed 90

The Animal Intrusion Detection and Classification system uses hybrid CNNs and IoT devices like PiCam and motion sensors to detect wildlife in real time. It was trained on datasets like Amur Tiger and Google Open Images, achieving high accuracy and adaptability in low-light environments. The solution is scalable and suitable for real-time field applications [2]. Still, it only detects predefined animals and struggles in dynamic or dense areas, causing false detections. It also lacks adaptive learning for new species and requires more resources for large-scale use. Enhancing scalability and species generalization can improve system robustness [2].

The Wild Animal Intrusion Detection Model uses ultrasonic sensors and ESP32- CAM for real-time alerts to detect animal movement in farms. Images and alerts are sent to farmers via an IoT app, and alarms deter animals instantly. The system ensures prompt responses and improves agricultural protection [3]. Despite its effec- tiveness, the ESP32-CAM lacks infrared and wide-angle support, reducing low-light performance. Its dependence on predefined paths and limited field testing impacts real- world adaptability. Enhancements like better imaging and terrain-aware deployment are needed [3].

The AI and ML-based system for agricultural farms uses MobileNet SSD with OpenCV for animal detection. It triggers alarms and sends SMS/email alerts with time and location. IoT integration enables remote monitoring, offering a cost-efficient and scalable solution for crop protection [4]. It struggles with dense vegetation, needs internet for alerts, and can't classify complex animal behavior. High traffic may delay processing. Nonetheless, it outperforms older systems in sustainability and cost-efficiency [4].

Another version of the same AI system highlights its use of MobileNet SSD on MS COCO dataset with OpenCV for real-time video-based detection. It triggers alarms and uses SMS/email to alert farmers. Cloud and IoT integration enhance flexibility and reduce costs versus electric fences or manual guarding [5]. Limitations include poor accuracy with occlusions, internet dependency, and inability to analyze animal behavior. Energy use for constant operation is high, but the system still offers better scalability and environmental benefits [5].

Digital Borders introduces a scalable deep learning system using MobileNetv2-SSD for animal detection and ResNet50 for re-identification. It identifies species like tigers and elephants and uses movement direction to trigger targeted deterrents. A central server manages identity and alerts in near real-time [6]. However, the system suffers from false positives, low fps (2–3), and lower accuracy for less-visible species. External threats like camera damage or animal habituation also reduce effectiveness. Future work can improve adaptability and robustness [6].

This IoT-based intrusion system uses Raspberry Pi, ESP8266, and PiCam with SSD and R-CNN models for detection. SSD gives better real-time performance (mAP: 89.32%) and alerts are sent using Twilio API. LED and buzzer deterrents support non-lethal repulsion. It works well in various light conditions [7]. Still, it uses a small dataset (300 images), limiting generalization. Lighting and connectivity issues can affect reliability, and it lacks support for multi-animal intrusions. Improvements in dataset and model diversity would enhance performance [7].

This SVM-based system uses Gabor filters and watershed segmentation for clas- sifying animal threats. A linear SVM achieves 99.48% best-case and 54.32% average accuracy. It's efficient and requires less training data than deep learning models, ideal for small setups [9]. Yet, it only detects dogs and Nilgai and struggles under low visibil- ity. A small dataset affects generalization, and no deterrents are included. Expanding species coverage and integrating repulsion tools could increase practicality [9].

Advances in deep learning and IoT have enhanced animal detection, classifica- tion, and tracking in wildlife monitoring. Hybrid neural networks, CNNs, and edge AI offer robust identification and environmental adaptability. Tools like thermal imaging and laser detection have improved efficiency in varied conditions [10]. Despite this, most systems lack real-time repulsion capabilities and consistency across challenging environments. Scalability in remote areas and the absence of dynamic responses limit applicability. Addressing these gaps is crucial for broader ecological use [10].

3. Methodologies

In Design and Development of a Variable Ultrasonic Frequency Generator for Rodents Repellent, the authors developed a device to repel rodents by generating ultrasonic frequencies within a range of 20–125 kHz. The circuit design was structured into five components: power supply, input, frequency generator and regulator, oscillator, and output unit. The power supply converted 220V AC to 5V DC through a transformer and rectification circuitry. A Passive Infrared (PIR) sensor detected rodent presence by identifying infrared radiation emitted from thermal bodies, triggering ultrasonic sound emission. Frequency generation was controlled using an Arduino Nano microcontroller, ensuring precise operation across the ultrasonic range.

The system was evaluated under laboratory conditions to assess detection effi- ciency, frequency precision, and power consumption. The PIR sensor's detection capabilities and the accuracy of ultrasonic signal output were validated using an oscilloscope. An LCD display was integrated to provide real-time frequency output, allowing the authors to monitor and refine system performance. This methodi- cal approach demonstrated the device's effectiveness and reliability in creating an acoustically hostile environment for rodents. [1].

Fig. 3: A block diagram of devoloped Repellent .

Figure 3, illustrates the operational flow of the Variable Ultrasonic Frequency Generator for Rodent Repellent system. The process begins with the Power Supply, which converts 220V AC to a stable 5V DC to power the circuit.

Algorithm Ultrasonic Frequency Generator Methodology

Input: Power source and rodent detection signals

Output: Ultrasonic frequencies for rodent repelling

Initialize: System components including PIR sensor, Arduino Nano, and ultra- sonic generator

▷ System Setup

Connect power supply to convert 220V AC to 5V DC.

Integrate PIR sensor for rodent detection based on infrared radiation.

Configure Arduino Nano to generate and regulate ultrasonic frequencies (20–125 kHz).

Design circuit layout for frequency generation, regulation, and output.

▷ Operation Phase

while System is active **do**

Detect rodent presence using the PIR sensor.

Trigger ultrasonic frequency generation upon detection.

Display real-time frequency output on the LCD screen.

Evaluate frequency precision using an oscilloscope.

end while

▷ Testing and Validation

if Frequency matches the specified ultrasonic range **then**

Confirm accuracy and effectiveness in repelling rodents.

Monitor power consumption to ensure energy efficiency. **else**

Adjust frequency parameters using Arduino for recalibration.

end if

▷ Post-Processing

Record performance metrics such as detection accuracy and response time.

Save results and reset the system for the next operational cycle.

The Animal Intrusion Detection and Classification system integrates Convolutional Neural Networks (CNNs) with IoT technologies for real-time monitoring and threat mitigation. Motion sensors trigger PiCam to capture and preprocess images, which are analyzed by the CNN model to classify entities using convolutional, pooling, and fully connected layers. The system responds with notifications or tailored deterrent sounds to mitigate risks. Trained on datasets like Amur Tiger Re-identification and Google Open Images V6, it achieves high accuracy through tenfold cross-validation and dropout layers. By leveraging deep feature extraction, it ensures robust performance in diverse conditions, including dynamic backgrounds, varied poses, and low-light scenarios.[2].

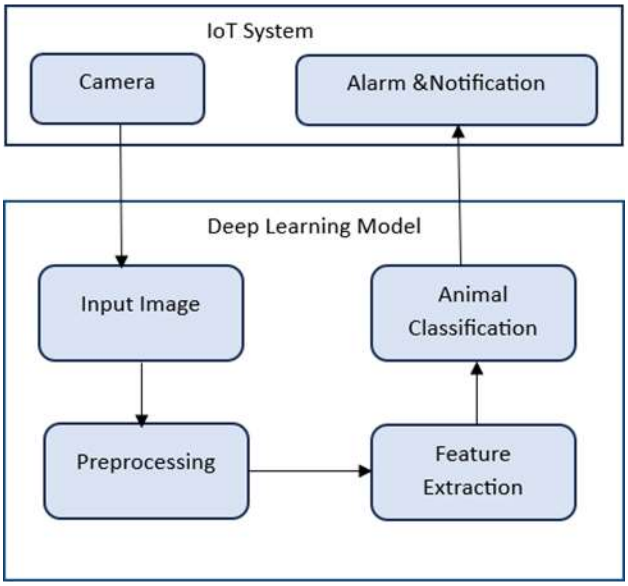

Fig. 4: Overview of System.

Figure 4, illustrates the sequence of the Animal Intrusion Detection and Classifi- cation system, where images captured by the IoT-enabled camera are first input into the system. These images undergo preprocessing, including resizing and normaliza- tion, to enhance the subsequent feature extraction process. The deep learning model then extracts critical spatial features from the images, which are utilized by the clas- sification module to identify the intruding animal. Upon successful classification, the system triggers alarm and notification mechanisms to alert stakeholders or deter the animal through tailored responses. This integrated IoT and deep learning approach ensures real-time, accurate detection and classification of animal intrusions, even under dynamic and complex environmental conditions.

The Implementation of a Wild Animal Intrusion Detection Model Based on Inter- net of Things employs a combination of ultrasonic sensors, an ESP32-CAM module, and IoT-based communication to detect and manage wild animal intrusions in agri- cultural fields. Ultrasonic sensors positioned at field boundaries detect motion and measure distances, sending signals to Arduino Uno boards, which process the data and coordinate responses via NRF24L01 wireless modules. A mobile E-vehicle prototype equipped with an ESP32-CAM module captures high-resolution images of intruders, dynamically adjusting the camera angle using a servo motor for optimal coverage. Infrared sensors enable the vehicle to navigate predefined paths, ensuring consistent monitoring. Captured images are transmitted to the Blynk IoT application, which provides real-time alerts to farmers while simultaneously activating an audible alarm to deter intruders. A Real-Time Clock (RTC) module regulates the vehicle's opera- tion, ensuring timely and efficient responses. This system integrates IoT technologies and automated mobility to offer a cost-effective and scalable solution for mitigat- ing human-wildlife conflicts, significantly improving field coverage and response time compared to traditional static monitoring methods.[3].

The AI-Based Surveillance System for Animal Detection and Alarm Activation combines computer vision and pre-trained deep learning models for real-time ani- mal detection and deterrence in agricultural fields. Using the MobileNet SSD model, trained on the MS COCO dataset, and the OpenCV library, it processes live video feeds from strategically placed cameras. The system triggers alarms to deter animals and sends alerts via SMS and email with intrusion details. Leveraging cloud-based ser- vices and IoT integration, it ensures scalability, connectivity, and ease of deployment. Cost-effective and efficient, the system minimizes wildlife harm, protects crops, and significantly outperforms traditional deterrence methods with enhanced accuracy and reliability. [4].

The above algorithm outlines the process of detecting and repelling animals in agricultural fields using a real-time AI-based system. It involves capturing video feeds, preprocessing frames, and detecting animals using the MobileNet SSD model inte- grated with OpenCV. Upon detection, the system activates a siren to deter the animal and sends alerts with intrusion details to the farmer via SMS and email. Additionally, it logs detection data to the cloud for analysis and future improvements.

The methodology in Digital Borders: Design of an Animal Intrusion Detection System Based on Deep Learning employs MobileNetv2-SSD for object detection and ResNet50 with Triplet Loss for animal re-identification. The MobileNetv2-SSD model, fine-tuned with datasets of tigers, jaguars, and elephants, is quantized to opti- mize deployment on resource-efficient devices like Raspberry Pi. Motion-activated cameras detect movement and process images locally, while re-identification is per- formed by extracting feature vectors from detected animals using ResNet50, enabling cross-camera tracking and open-set identification. The system integrates Euclidean distance-based metrics for identity matching and triggers species-specific deterrents, such as flashing lights and sound alarms. This architecture ensures energy efficiency, scalability, and adaptability for real-world deployment scenarios.[6].

Algorithm AI-Based Animal Detection and Repulsion System

Require: Live video feed from strategically placed cameras.

Ensure: Animal detection, activation of deterrence mechanism, and alert notification.

1: **Initialize the System**

2: Set up cameras at farm entry points.

3: Load the pre-trained MobileNet SSD model and configure OpenCV for processing video frames.

4: Establish connectivity with cloud-based services and IoT components for alerts and data storage.

5: **while** system is active **do**

6: **Video Frame Capture:** Capture real-time video feed from cameras.

7: Extract frames for analysis.

8: **Preprocessing:**

9: Convert frames to the required format for the detection model.

10: Normalize input images to match the model's input requirements.

11:**Animal Detection:**

12: Pass the preprocessed frame through the MobileNet SSD model.

13: Identify and classify objects in the frame.

14: **if** an animal is detected **then**

15: Extract detection details (bounding box, location, confidence score).

16: **Trigger Alarm:** Activate the siren to repel the detected animal.

17: **Send Alert:** Compile intrusion details (time, location, and camera ID).

18: Send notifications via SMS and email to the farmer.

19: **Data Logging:** Store detection details in the cloud for future analysis.

20: **end if**

21: **end while**

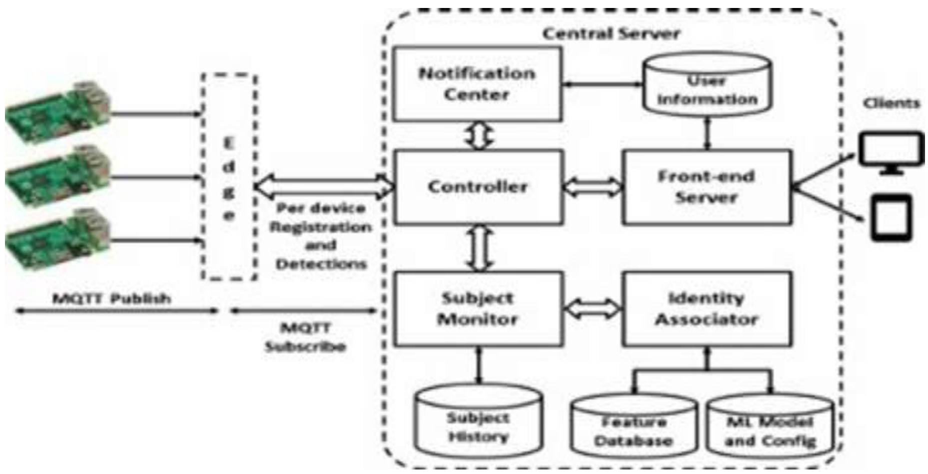

Fig. 5: Architecture of the System[6].

Figure 5, demonstrates an IoT-based architecture using MQTT for communication between edge devices and a central server. Edge devices publish detection data, which is processed by the server's controller. The central server integrates modules like the Subject Monitor for tracking, the Identity Associator for matching features with a database, and the Notification Center for alerts. Data is stored in the Subject History and Feature Database, while machine learning models in the system support identi- fication and decision-making. Clients access information through a front-end server, enabling real-time monitoring and alerts.

The Application of IoT and Machine Learning in Crop Protection Against Animal Intrusion proposes an IoT-based system using a Raspberry Pi controller, ESP8266 Wi-Fi module, Pi Camera, LED lights, and a buzzer, powered by a 12V battery. Real-time images captured by the Pi Camera are processed using machine learning algorithms, including Region-based Convolutional Neural Network (R-CNN) and Sin- gle Shot Detector (SSD), to detect and classify animal intrusions. SSD, with its faster and more accurate detection, outperformed R-CNN. The system triggers alerts via LED lights, a buzzer, and notifications to farmers through Twilio API, enabling timely action and demonstrating the potential of IoT and AI in enhancing crop protection. [7].

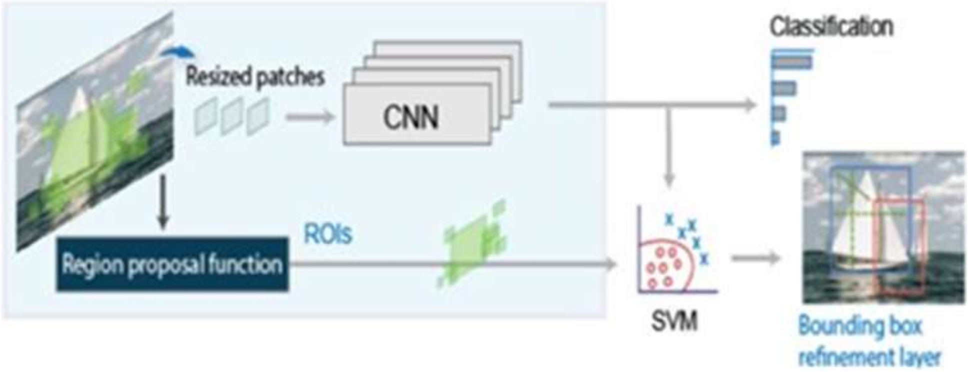

Fig. 6: Object detection using R-CNN detector architecture[7].

Figure 6, illustrates a region-based object detection system, such as R-CNN. It begins with resizing input image patches generated by a region proposal function to identify regions of interest (ROIs). These patches are passed through a Convolutional Neural Network (CNN) for feature extraction. The features are then classified using a Support Vector Machine (SVM), and bounding box refinement adjusts the detected object boundaries for accurate localization.

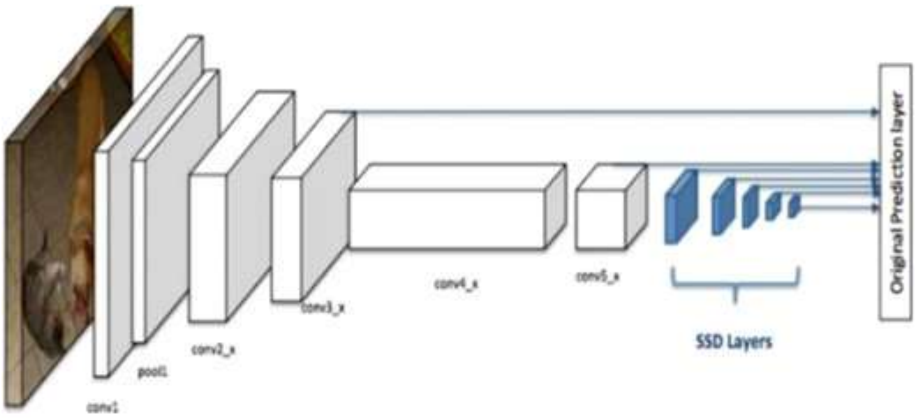

Fig. 7: Object detection using SSD detector architecture[7].

Figure 7, illustrates the architecture of a Single Shot MultiBox Detector (SSD) used for object detection. The input image passes through a series of convolutional layers, each extracting features at different levels. After feature extraction, additional layers, known as SSD layers, generate predictions for object classes and bounding boxes at multiple scales. The final output layer combines these predictions for accu- rate object detection.

The above algorithm outlines an IoT and AI-based system for crop protection against animal intrusion. It begins with initializing the Raspberry Pi as the central controller, interfacing hardware components like the Pi Camera, ESP8266 Wi-Fi module, LED lights, and a buzzer. Real-time images captured by the Pi Camera are preprocessed and analyzed using TensorFlow with R-CNN and SSD models for animal detection and classification. Upon detecting an animal, deterrence mechanisms (LED lights and buzzer) are activated, and alerts are sent to farmers using the Twilio API. Detection details, including time and classification, are logged in the cloud for moni- toring and analysis. This process ensures continuous real-time protection of crops.

The study Wild Animals Intrusion Detection using Deep Learning Techniques developed a system to detect and deter wildlife intrusions in agricultural fields using a convolutional neural network (CNN). A dataset comprising images of elephants, boars, and monkeys with diverse backgrounds, lighting conditions, and poses was col- lected and preprocessed with techniques like rescaling, shear transformation, zooming, and flipping to enhance variability and reduce overfitting. The CNN, implemented using Python with Keras and OpenCV, achieved a validation accuracy of 98% over 40 epochs, showcasing its effectiveness in accurately classifying the animal classes. Deployed in real-time, the system processed live video feeds to detect intrusions and triggered species-specific repellent sounds using the Playsound library, providing a humane, efficient solution to wildlife intrusion challenges in agricultural environments. [8].

Algorithm Wild Animals Intrusion Detection and Repulsion System

Require: Image dataset for training and live video feed from surveillance cameras.

Ensure: Real-time animal detection, repulsion using deterrent sounds, and logging of detected intrusions.

1: **Initialize the System:**

2: Set up the hardware components: surveillance camera, computer, and speakers.

3: Load the pre-trained Convolutional Neural Network (CNN) model.

4: Prepare the environment for real-time image processing using OpenCV and Playsound libraries.

5: **while** system is active **do**

6: **Image Capture:** Capture real-time frames from the surveillance camera.

7: **Preprocessing:**

8: Convert captured frames to match the model's input dimensions (e.g., 64x64 pixels).

9: Normalize pixel values to the range [0, 1] for consistent processing.

10: **Animal Detection:**

11: Pass the preprocessed frame through the CNN model for classification.

12: **if** an animal is detected **then**

13: Retrieve detection details (animal class and confidence score).

14: **Trigger Repulsion Mechanisms:**

15: Play species-specific deterrent sounds using the Playsound library to repel the animal.

16: **Send Notifications (Optional):**

17: Log the intrusion details, including detection time and animal class, for further analysis.

18: **Data Logging:**

19: Store detection details in a local or cloud database for monitoring and future enhancements.

20: **end if**

21: **end while**

The paper, Support Vector Machine with Gabor Features for Animal Intrusion Detection in Agriculture Fields, presents a machine learning framework for detect- ing and classifying animals to prevent crop damage. It addresses challenges such as noise, overlapping objects, variable lighting, and partial visibility in real-world agricultural environments. The process begins with image preprocessing to enhance quality by reducing noise and preparing the data for further analysis. For segmen- tation, the marker-based watershed algorithm is utilized to accurately delineate object boundaries, even in complex scenarios where objects overlap or blend into the background.Feature extraction employs a 2D Gabor filter bank, designed to capture critical texture and frequency features necessary for differentiating animal types.

These features are robust to variations such as noise, rotation, and occlusion, ensur- ing reliable performance. The extracted features are then classified using a Linear Support Vector Machine (SVM), which is trained on a diverse dataset augmented with real-world variations to improve its generalization capabilities. The system demonstrates high accuracy and resilience under challenging conditions, making it an effective solution for detecting animal intrusion in agricultural fields. By addressing environmental complexities, this framework provides farmers with a practical tool to safeguard crops and enhance productivity.[9].

Algorithm Animal Intrusion Detection using SVM and Gabor Features

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Require: Image dataset of animals

Ensure: Classification of detected animals as threats or non-threats

1: **Image Acquisition:** Capture field images using a camera.

2: **Preprocessing:**

3: Convert images to grayscale and apply *Otsu's thresholding*.

4: Perform *morphological opening* and *distance transform* to extract foreground.

5: **Segmentation:** Apply the *watershed algorithm* to isolate objects.

6: **Feature Extraction:**

7: Use a 2D Gabor filter bank with parameters (λ, θ, σ, γ) to extract features.

8: Compute the *mean* and *standard deviation* of filtered outputs.

9: **Classification:**

10: Train a *Linear SVM classifier* with labeled feature vectors.

11: Classify test images into:

- Threat animals (e.g., Nilgai)
- Non-threat animals (e.g., dog)

12: **Threat Notification:** Trigger an alert (e.g., message to farmer) for threat detection.

The above algorithm for animal intrusion detection begins by capturing images of agricultural fields using a camera. Preprocessing steps include converting images to grayscale, applying Otsu's thresholding, and using morphological operations to remove noise and isolate the foreground. Segmentation is performed with the watershed algo- rithm to separate individual objects. Features are extracted using a Gabor filter bank, which computes mean and standard deviation values for classification. A Linear SVM classifier is trained on labeled data and used to classify animals as threats (e.g., Nilgai) or non-threats (e.g., dog). If a threat is detected, an alert system notifies the farmer to take action.

4. Implementation Details

The implementation of the variable ultrasonic frequency generator involved assembling the circuit on a printed circuit board and integrating components such as a power supply unit, PIR sensor, Arduino Nano, relay module, and acoustic emitter. The power supply converted 220V AC to 5V DC to power the device, while the PIR sensor detected rodents via infrared radiation. Upon detection, the Arduino generated ultrasonic frequencies between 20–125 kHz, emitted through multimedia speakers to repel the animals. A relay module ensured accurate emission timing, and an LCD displayed the output frequency in real time. The system was tested in a lab setting to validate accuracy, range, and power efficiency [1].

For Animal Intrusion Detection and Classification, TensorFlow and Keras were used with custom Python functions for feature extraction. OpenCV handled image capture and preprocessing. A Raspberry Pi, integrated with sensors and cameras, enabled real-time motion detection and image acquisition. A convolutional neural network processed spatial and temporal features, facilitating accurate classification. A user interface allowed real-time monitoring and notifications for stakeholders [2].

The wild animal intrusion detection system incorporated ultrasonic sensors to detect motion, which was relayed via NRF24L01 modules to an Arduino Uno. An ESP32-CAM on a mobile E-vehicle captured intruder images and followed predefined paths using IR sensors. Images were transmitted to the Blynk app for alerts, and an audible alarm deterred animals. A Real-Time Clock ensured efficient operation [3].

An AI-Based Surveillance System used MobileNet SSD and OpenCV to process live video from cameras at farm entry points. Upon detecting animals, the system activated a siren and sent alerts via SMS and email, detailing intrusion time and cam- era location. Cloud services supported data storage and alerts, while IoT components ensured integration and remote accessibility [4].

In Animal Species Recognition, CNNs were built and trained using Python libraries such as TensorFlow or PyTorch. Images were resized to 224×224 pixels, and sepa- rate binary and multi-class models were trained. Data augmentation helped address class imbalance, and confidence thresholding filtered uncertain predictions. GPU acceleration likely supported the training of high-resolution images [5].

The Digital Borders system used motion-activated cameras, Raspberry Pi devices, and a central server. Quantized MobileNetv2-SSD models ran on edge devices to detect specific animals like tigers and elephants. A ResNet50 model with Triplet Loss handled re-identification by extracting feature vectors. Movement direction was used to trigger species-specific deterrents such as lights or alarms [6].

In another IoT-based system, a Raspberry Pi 4 with an ESP8266 Wi-Fi module and Pi Camera enabled image capture under varied lighting. TensorFlow models (R-CNN and SSD) were used for object detection, with SSD providing faster, more accurate results. Alerts were sent using Twilio API, while LEDs and buzzers deterred animals. Python managed all workflows and hardware control [7].

The Wild Animals Intrusion Detection system was implemented using Keras for CNN model training and OpenCV for real-time frame capture. Data augmentation techniques such as rescaling, shearing, and flipping improved model robustness. The Playsound library triggered deterrent sounds when an animal was detected, offering a scalable and effective solution [8].

Another approach involved preprocessing field images with Otsu's thresholding and morphological operations for noise reduction. A marker-based watershed algorithm segmented the objects, and Gabor filters extracted texture features. These were clas- sified using a Linear SVM trained on images of Nilgai and dogs, including augmented variations. Python and OpenCV supported the end-to-end implementation [9].

4.1 Evaluation Metrics

In Design and Development of a Variable Ultrasonic Frequency Generator for Rodents Repellent, evaluation metrics included detection accuracy (PIR sensor range: 4.5m), frequency precision (oscilloscope comparison), coverage range, response time, and power consumption, ensuring reliable and efficient operation [1].

In Animal Intrusion Detection and Classification, accuracy, precision, recall, and F1 score measured the CNN model's performance. The system demonstrated robustness under varying conditions, handling different lighting, backgrounds, and animal poses effectively [2].

In AI-Based Surveillance System for Animal Detection and Alarm Activation, pre- cision, recall, and F1-score assessed detection accuracy, while frame processing rate (FPS) and alert accuracy ensured real-time efficiency and minimal false alarms [4].

In Animal Species Recognition Using Deep Learning, accuracy was the primary metric, achieving 99.8% for binary classification and 97.6% for multi-class species identification. Confidence thresholding improved prediction reliability by filtering low- probability classifications [5].

In Digital Borders, evaluation included detection accuracy, false positive rate (FPR), and re-identification using Top-1/Top-5 rank accuracy. Frame processing time (FPS) ensured real-time feasibility in object detection and tracking [6].

In Application of IoT and Machine Learning in Crop Protection Against Ani- mal Intrusion, mean Average Precision (mAP) measured detection performance (SSD: 89.32%, R-CNN: 85.22%). Real-time efficiency was evaluated using Twilio API alerts, LED indicators, and a buzzer [7].

In Wild Animals Intrusion Detection using Deep Learning Techniques, the sys- tem achieved 98% validation accuracy. Real-time detection reliability was ensured by comparing live video predictions with training dataset ground truth [8].

In A Support Vector Machine with Gabor Features for Animal Intrusion Detec- tion in Agriculture Fields, accuracy was assessed under varying conditions. The model achieved 99.48% best-case accuracy and 54.32% average accuracy across noise, rotation, and partial visibility tests [9].

4.2 Performance Analysis

The Variable Ultrasonic Frequency Generator achieves precise rodent repulsion (±0.428% frequency error) within 4.5 meters under controlled conditions, proving effective in lab environments. It outperforms chemical repellents in safety but lacks validation in real-world scenarios with variable rodent behavior and obstructions [1]. The Animal Intrusion Detection and Classification system delivers 99.6% and 95.6% accuracy on two datasets, handling dynamic environments and lighting varia- tions well. However, its performance drops with non-predefined animals or crowded scenes, limiting scalability. It surpasses traditional methods in structured settings but needs improvement for broader species and regions [2].

The proposed ultrasonic sensor-based system with ESP32-CAM captures clear images and enables real-time IoT alerts. Its mobile E-vehicle setup enhances coverage, but poor low-light performance, limited scalability in large fields, and lack of infrared support reduce adaptability [3].

The AI-Based Surveillance System achieves 88.5% accuracy and 18 FPS using MobileNet SSD, offering efficient real-time detection. Cloud notifications support quick alerts, but dependence on internet connectivity and performance issues in dense vegetation are notable drawbacks [4].

The Animal Species Recognition system attains 99.8% and 97.6% accuracy for human-animal distinction and species ID, respectively, using a CNN. While robust in varied conditions, it struggles with low-quality data and real-time deployment due to dataset size and lighting issues [5].

The Digital Borders system pairs MobileNetv2-SSD (92.56% accuracy) with ResNet50 (99.6% Top-1 accuracy) for detection and re-identification, excelling with tigers. Limited training data for other species and slow processing (2–3 FPS) hin- der broader application. Reducing false positives and expanding datasets are key to improvement [6].

An SSD-based IoT system achieves 89.32% mAP with faster detection than R- CNNs. It integrates well with IoT but relies on a small dataset, limiting generalization. Expansion and optimization are needed for larger agricultural use cases [7].

The Wild Animal Intrusion Detection system using deep learning achieves 88% validation accuracy and adapts to varied lighting and backgrounds. However, hardware limitations affect real-time training and speed. Despite this, its scalability makes it a viable alternative to older systems [8].

An SVM and Gabor filter-based system offers efficient intrusion detection with high accuracy and minimal training data. While effective in real-time and low-resource settings, performance declines in poor visibility or noisy environments, and species generalization remains limited [9].

Table 1: Performance Analysis Table

Title	**Quantitative Analysis**	**Qualitative Analy- sis**	**Comparison with Alternatives**
Design and Development of a variable	Frequency range: 20–125 kHz (±0.428% error),	Cost-effective, eco-friendly, non-invasive; adaptable	Safer and non-toxic compared to chemical repel-

ultrasonic fre- quency generator for rodents repellent[1]	max detection: 4.5 m, 90% accuracy.	to various rodent species.	lents; customizable and avoids rodent habituation unlike static devices.

Title	**Quantitative Analysis**	**Qualitative Analy- sis**	**Comparison with Alternatives**
DeepAID: A Design of Smart Animal Intru- sion Detection and Classifica- tion Using Deep Hybrid Neural Networks[2]	Achieved 99.6% accuracy on Ani- mals Detection Images, 95.6% on Google Open Images V6, and 92% on Amur Tiger datasets, with high relia- bility in real-time processing.	Robust under diverse conditions, includ- ing dynamic scenes, varied animal poses, and lighting changes, with effective alert and deterrence mechanisms.	Outperformed traditional detection methodsin accuracy and adaptability, but scalability and detection of non- predefined species remain challenges.
Implementation of a Wild Animal Intrusion Detec- tion Model Based on Internet of Things[4].	High detection accuracy with ultrasonic sen- sors and reliable image capture. Real-time alerts and effective alarms.	Reliable detection and notification but limited in low-light and uneven terrains.	Better coverage than static sys- tems but lacks advanced imaging and scalability.
Agricultural Farms Utiliz- ing Computer Vision (AI) And Machine Learning Tech- niques For Animal Detec- tion And Alarm Systems[4].	Detection accu- racy of 88.5% with 18 FPS real-time processing. Alerts delivered reliably, minimizing false positives.	Integrates AI and IoT for cost-effective, scalable, and wildlife-friendly monitoring and deterrence.	More cost-effective and eco-friendly than traditional methods, with superior accuracy and reliability.
Animal Species ecognition Using Deep Learning[5]	Achieved 99.8% accuracy in detecting humans vs. animals and 97.6% in iden- tifying animal species, varying by class.	Robust under diverse conditions like low light and occlusion; confidence threshold- ing improved classifi- cation reliability.	Outperformed traditional feature-based methods and earlier CNN studies in accuracy but faced challenges with real-time pro- cessing and dataset dependency.

Title	**Quantitative Analysis**	**Qualitative Analy- sis**	**Comparison with Alternatives**
Digital Borders: Design of an Ani- mal Intrusion Detection System Based on Deep Learning[6]	Detection accu- racy: Tigers (80%), Jaguars (89.47%), Elephants (92.56%). Re-identification accuracy: Tigers (99.6%), Jaguars (86.2%), Elephants (61.7%).Frame rate: 2–3 fps.	Robust detection and tracking; effective deterrence.	Scalable and efficient but higher false positives and lower accuracy for less-represented species..
Application of IoT and Machine Learning in Crop Protection Against Animal Intrusion[7]	Achieved an mAP of 89.32% for SSD and 85.22% for R-CNN using a dataset of 300 images across five animal classes.	Reliable real-time performance with fast detection and effective alerts.	Outperformed tra- ditional IoT and ML methods in accuracy, speed, and scalability.
Wild Animals Intrusion Detection using Deep Learning Techniques[8]	Achieved 98% validation accu- racy with 1,200 images per class.	Effective real-time detection of boars, elephants, and monkeys in varied conditions.	More scalable and efficient than hardware- intensive or manual surveillance methods.
A Support Vec- tor Machine with Gabor Features for Animal Intru- sion Detection in Agriculture Fields[9]	Best-case accu- racy of 99.48%, average accuracy of 54.32%.	Robust in handling noise, rotation, and partial visibility.	More efficient than alternatives, using fewer train- ing images but struggles with low visibility

4.3 Challenges and Limitations

The recent advancements in animal detection, identification, and repellent methods have demonstrated significant progress in addressing human-wildlife conflicts, particularly in agri- cultural and ecological contexts. However, these developments are accompanied by notable challenges and limitations. While modern technologies such as IoT, deep learning, and ultrasonic systems have enhanced the accuracy and efficiency of detection and deterrence mechanisms, issues related to scalability, environmental adaptability, and cost-effectiveness persist. The integration of diverse sensors, machine learning models, and imaging technologies highlights the potential for innovative solutions but also underscores the need for addressing the inherent limitations in real-world deployment. In ”Variable Ultrasonic Frequency Gener- ator,” testing was confined to controlled laboratory environments, restricting the evaluation of performance under real-world conditions, such as fluctuating temperatures, humidity, and obstacles affecting ultrasonic wave propagation. Furthermore, the device’s long-term dura- bility and the potential for rodent habituation to ultrasonic frequencies were not assessed. The reliance on a PIR sensor introduced detection limitations beyond 4.5 meters or at cer- tain angles. Scalability remains another challenge, as the design’s cost-effectiveness has not been proven viable for large storage facilities or open agricultural spaces, underlining the need for further real-world testing and scalability optimization.[1].Conversely, The ”DeepAID System” shows promise in animal identification but is constrained by predefined animal classes, limiting generalizability in diverse ecological settings. High deployment costs and reduced detection accuracy in densely populated areas challenge scalability. Reliance on ther- mal cameras further raises costs, limiting accessibility. Expanding datasets and integrating cloud-based processing could improve versatility and reduce these limitations[2].

The ”Wild Animal Intrusion Detection System” using the ESP32-CAM module is innova- tive but faces performance issues in low-light conditions due to a lack of infrared capabilities. The reliance on predefined pathways reduces adaptability to irregular terrains, and scala- bility is restricted without significant modifications. Enhancements in imaging technology and scalable architectures are needed to improve its usability across diverse landscapes[3]. The ”AI-Based Surveillance System for Animal Detection and Alarm Activation” offers cost- effective solutions but struggles with dense vegetation and occlusions, reducing detection accuracy. Reliance on external datasets like MS COCO limits adaptability to localized con- ditions. Internet connectivity requirements for cloud-based notifications pose challenges in remote areas. Optimizations in system reliability and adaptability are crucial for diverse agricultural environments.[4].

”Animal Species Recognition Using Deep Learning” is limited by its reliance on large, labeled datasets, reducing accuracy for certain species like moose. Environmental factors such as poor lighting and occlusion hinder feature extraction, while computational demands limit real-time applicability. Confidence thresholding improves precision but risks disregard- ing valid low-confidence predictions. Efficient algorithms and better data augmentation are necessary for improvement.[5] The ”Digital Borders System” excels in wildlife monitoring but faces issues like limited dataset diversity, leading to detection inaccuracies for less-distinctive species. False positives in cluttered environments and low frame rates of 2–3 fps affect relia- bility. Operational challenges, including physical damage and theft in remote areas, require system refinement for broader deployment and resilience[6]

The integration of IoT and machine learning in ”Application of IoT and Machine Learn- ing in Crop Protection Against Animal Intrusion” shows promise but is limited by small datasets and slower processing times in R-CNN models. Dependence on adequate lighting restricts operations in poor visibility. Larger datasets, improved algorithms, and robust hard- ware are essential for scalability and reliability in diverse scenarios [7]. In ”Wild Animals Intrusion Detection Using Deep Learning Techniques,” challenges arise from the diversity of animal appearances and environmental conditions. Accuracy declines with blurred or low-resolution images, especially in poor visibility. Computationally intensive CNNs require substantial resources, posing deployment challenges on low-cost hardware. Data augmen- tation and efficient models are needed to enhance real-time applications [8]. The ”Animal Intrusion Detection in Agricultural Fields Using SVM and Gabor Features” system is efficient but struggles with occlusion and high-noise environments, reducing detection accuracy. A small training dataset limits generalizability, and extreme variations in brightness or contrast affect performance. Improving dataset diversity and model architecture is vital for better adaptability in challenging scenarios [9].

Altogether, these animal detection, identification, and repellent systems illustrate both the advancements and persistent limitations across various contexts. Moving forward, inte- grating adaptable, hybrid approaches that combine advanced imaging, IoT technologies, and

deep learning can address challenges related to scalability, environmental adaptability, and cost-effectiveness. Such comprehensive solutions are essential to enhance the reliability and applicability of these systems in diverse agricultural and ecological scenarios.

5. Conclusions and Future Scope

The combined findings from these studies highlight the significant advancements in animal intrusion detection, identification, and repellent systems, addressing the pressing challenges of human-animal conflicts and wildlife management. Leveraging IoT, machine learning, and deep learning technologies, these systems demonstrate the evolving capabilities of integrating real-time monitoring, species-specific deterrence, and scalability for diverse environments.

Systems using ultrasonic frequencies, such as the rodent repellent device in ”The Design and Development of a Variable Ultrasonic Frequency Generator for Rodents Repellent,” highlight the potential for eco-friendly, non-invasive solutions. These devices achieve high detection accuracy and efficient power consumption but require further testing in uncon- trolled environments. Enhancements in field applications, detection range, and integration with IoT and renewable energy could improve their scalability and effectiveness, particularly in agricultural settings.

Deep learning and computer vision approaches, as seen in ”Animal Intrusion Detection Using Hybrid Convolutional Neural Networks” and ”Agricultural Farms Utilizing Computer Vision Techniques,” demonstrate robust capabilities in detecting and repelling intrusions in real-time. With technologies like MobileNet SSD and OpenCV, these systems ensure humane deterrence while offering scalability and remote accessibility. Future directions include addressing detection challenges in dense vegetation, improving offline capabilities, and incorporating adaptive learning for better generalizability.

Building on these insights, future research should focus on enhancing the robustness and scalability of these systems while addressing species-specific and environmental challenges. By combining advanced detection methods with humane repulsion mechanisms, supported by IoT and cloud frameworks, these systems hold promise for applications in agriculture, wildlife management, and mitigating human-animal conflicts on a broader scale.

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