AI-Based Agricultural Risk Management System For Farmer Well-Being

Kavitha P
Dept. of Information Science and Engineering
Global Academy of Technology
Bengaluru, Karnataka, India

Deeksha S
Dept. of Information Science and Engineering
Global Academy of Technology
Bengaluru, Karnataka, India

Nikitha V
Dept. of Information Science and Engineering
Global Academy of Technology
Bengaluru, Karnataka, India

Akshatha Preeth P
Dept. of Information Science and Engineering
Global Academy of Technology
Bengaluru, Karnataka, India

***Abstract*— Animal intrusion refers to the unauthorized presence of animals in areas such as farms, forests, or urban zones, often leading to damage, safety risks, or property loss. These incidents, frequently caused by wild or domestic animals, necessitate rapid and reliable monitoring systems. The integration of Artificial Intelligence (AI) has greatly enhanced these systems by improving accuracy, speed, and automation in surveillance. Machine Learning (ML) and Computer Vision (CV) approaches enable automatic detection and monitoring of animal movements via camera feeds or sensor data, assisting in wildlife protection and security measures.**

This study explores a deep learning-based approach to detect animal intrusions in diverse outdoor environments. Models like YOLOv5 and EfficientDet, trained using PyTorch and fine-tuned for real-time performance, are evaluated using key metrics such as accuracy, precision, recall, F1-score, and mean Average Precision (mAP). Among the tested models, YOLOv5 achieved the highest accuracy, with a mean mAP of 75.7%, indicating strong real-time detection capabilities. The findings confirm that object detection models based on deep Convolutional Neural Networks (CNNs) are highly effective in identifying both wild and domestic animals, supporting better wildlife monitoring and security systems.

***Keywords*— Deep Learning, CNN, YOLOv5, EfficientDet, Object Detection, Real-time Surveillance, Animal Classification, Intrusion Detection, Computer Vision**

I. Introduction

Globally, the agriculture and conservation sectors face serious threats from animal intrusions, which can lead to significant crop damage, economic losses, and ecological imbalances. Human–wildlife conflict has intensified due to rapid urbanization and expansion into natural habitats. Areas near forest borders, in particular, face frequent animal intrusions, leading to crop damage, property loss, and safety risks. Reports indicate that agricultural regions in countries such as India and parts of Africa and Southeast Asia face annual crop losses ranging from 10% to 30%, severely affecting national food security and local economies.

Traditional animal detection systems like human patrolling or fencing are often inefficient, labor-intensive, and risky. To address these challenges, modern AI technologies, particularly in the domains of Machine Learning and Computer Vision, offer advanced solutions. Deep learning techniques, especially models like YOLOv5 and EfficientDet, have shown excellent performance in identifying animal species from images and videos, enabling prompt alerts and reducing intrusion threats.

However, these models may underperform in complex, real-world environments due to varying light, weather, backgrounds, and animal postures. To overcome these issues, this study utilizes CNN-based models (YOLOv5 and EfficientDet) trained with PyTorch and refined for diverse outdoor scenarios. Data augmentation methods were applied to enhance model adaptability and robustness. Results show that YOLOv5 achieved the best detection accuracy, with a mean Average Precision (mAP) of 92.7%, confirming its effectiveness for real-time applications. This high performance indicates the model's strong ability to generalize across diverse environments and animal species. Its rapid processing speed and precision make it suitable for deployment in remote monitoring stations, forest borders, and agricultural zones. Furthermore, when integrated with IoT devices and cloud-based surveillance systems, YOLOv5 enables automated alerts and efficient response mechanisms, minimizing human involvement and ensuring timely action. Such advancements support proactive wildlife management and enhance the safety of both people and resources in vulnerable areas.

The trained model demonstrated a high mean Average Precision (mAP) of 92.7% on the test set, indicating its strong potential in field conditions. By integrating such systems with edge devices and surveillance cameras, real-time intrusion alerts can be generated, allowing farmers, forest officials, or security personnel to respond proactively. This research represents a significant step forward in the application of AI for environmental monitoring and agricultural protection, providing a scalable, accurate, and timely solution to mitigate the risks associated with animal intrusions.

The rest of this paper is organized into several sections: Section II discusses prior research and developments in the field of animal detection and surveillance; Section III explains the architecture of the proposed system along with the technical approach used; Section IV details the experimental findings and performance metrics; and finally, Section V summarizes the key outcomes of the study and proposes potential improvements for future work.

II. Related Work

The application of Artificial Intelligence (AI) in animal intrusion detection has emerged as a key research focus, especially in areas such as precision agriculture, habitat monitoring, and wildlife protection. Leveraging Machine Learning (ML) and Computer Vision (CV) technologies, modern systems are capable of identifying, categorizing, and tracking animals in real-time, thereby enhancing the overall monitoring process. Several research efforts have demonstrated the effectiveness of object detection models—particularly those using Convolutional Neural Networks (CNNs)—in identifying animals under varying environmental and lighting scenarios.

Kumar et al. [1] proposed an animal detection system using YOLOv3 on surveillance cameras deployed near forest edges, achieving rapid identification with minimal false positives. Their system demonstrated effective performance during both day and night, utilizing infrared and RGB imaging. Similarly, Shah and Patel [2] used the YOLOv4 architecture to detect intrusions in agricultural fields and reported a significant drop in crop damage incidents after deployment. The system was optimized for edge devices, enabling real-time alerts without cloud dependency.

Ghosh et al. [3] utilized the Faster R-CNN framework for detecting wildlife intrusions in farmlands located near forest areas, highlighting its precise object localization strengths. To improve detection in poor lighting, they incorporated thermal imaging into their approach. In a different study, Rathore et al. [4] combined classical background subtraction methods with the EfficientDet model to achieve a balance between lower computational cost and reliable detection accuracy.

In another study, Narayanan et al. [5] trained a lightweight MobileNet-based classifier to identify different animal species from video streams. Their focus was on low-cost embedded systems such as Raspberry Pi and NVIDIA Jetson Nano, which are suitable for deployment in remote or resource-constrained areas. Their model achieved 91.3% accuracy and successfully detected common intruders like wild boars, deer, and elephants.

Chaudhary et al. [6] proposed a hybrid approach that integrates YOLOv5 with motion tracking techniques to enhance the prediction of animal movements and optimize alert mechanisms. Their findings demonstrated improved responsiveness of the system in rapidly changing scenarios. In contrast, Islam et al. [7] presented a real-time surveillance solution using drones equipped with SSD (Single Shot Multibox Detector), enabling wide-area observation and autonomous navigation, thereby minimizing the need for manual intervention.

To address class imbalance and environmental diversity, researchers utilized advanced data augmentation strategies such as Generative Adversarial Networks (GANs) to generate synthetic samples for underrepresented animal categories. This enriched dataset played a crucial role in improving the overall model performance.

In their survey, Alqahtani et al. [9] reviewed over 80 publications related to AI in animal monitoring and identified a consistent trend toward CNN-based object detection as the preferred approach due to its accuracy and adaptability. However, they also noted recurring limitations, such as false positives due to background clutter or poor lighting, and emphasized the need for high-quality, annotated datasets.

Lastly, Pandey et al. [10] implemented a multi-sensor fusion system combining audio, thermal, and visual inputs, integrated with a CNN-based classifier to enhance accuracy in noisy or occluded environments. Their results showed a noticeable improvement in recall and reduced alert latency, making their system suitable for both security and wildlife conservation applications.

Collectively, the reviewed studies demonstrate that deep learning frameworks—especially models like YOLO, EfficientDet, and Faster R-CNN—are highly effective for real-time animal intrusion detection. Nevertheless, ensuring that these models perform reliably across varying environmental conditions remains a critical hurdle for broader implementation in practical scenarios.

III. Methodology

A. Dataset Description

In this study on animal intrusion detection, a diverse dataset was assembled using images sourced from the Kaggle Animal Detection dataset along with other publicly available wildlife monitoring repositories. The dataset comprises nearly 45,000 labeled images collected from surveillance equipment such as stationary cameras, motion-triggered trail cams, and aerial drones. These images span multiple environments, including various weather conditions, terrain types, and both daytime and nighttime scenarios. It features 15 distinct classes representing frequently observed domestic and wild animals—like elephants, deer, boars, monkeys, cattle, canines, felines, bears, leopards, foxes, rabbits, horses, goats, sheep, and humans (to filter false detections). Each image is annotated with category labels and bounding boxes, supporting efficient object detection model training. The dataset's comprehensive nature and realistic variation in intrusion contexts make it well-suited for developing a reliable, real-time detection system that minimizes errors and improves overall accuracy.

B. Data Preprocessing

Preparing data is a crucial initial phase in developing any machine learning or deep learning system. It involves converting unprocessed inputs into a standardized and clean format that enhances model training and performance. This process becomes particularly critical for image datasets, where variations or noise can negatively impact the learning accuracy and overall effectiveness of the model. Image preprocessing steps typically include resizing, normalization, and noise removal to ensure consistency across the dataset performance and accuracy. For the animal intrusion detection model, all input images were first resized to a standard dimension of (416, 416) to maintain uniformity across the training pipeline, ensuring compatibility with object detection architectures like YOLOv5. Pixel values were normalized to a range of **0 to 1** to accelerate convergence during training and improve computational efficiency.

Once trained and validated, the model can be deployed on edge devices or cloud systems for real-time intrusion detection, offering timely alerts to prevent damage to property, crops, or ecosystems. The animal intrusion detection system follows a structured deep learning approach, starting with the collection of surveillance data from sources like forest cameras, drones, or agricultural monitoring systems.

Figure 1: Batch division for the model training

Animal intrusion detection focuses on acquiring and annotating image or video data featuring animals—such as elephants, cows, and birds—within areas where access is restricted. This visual data undergoes a series of preprocessing steps, including resizing, normalization, and data augmentation, to enhance the accuracy and robustness of model training. After preprocessing, the dataset is divided into training, validation, and testing subsets, and formatted appropriately to be compatible with deep learning models like YOLO and Faster R-CNN. These object detection frameworks enable the system to identify and classify animal intrusions in real time, making them highly effective for security enforcement and wildlife observation purposes.

C. *Proposed Approach*

The proposed system for detecting animal intrusions follows a structured approach to efficiently process and evaluate visual input, enabling the real-time identification of animals such as elephants, cows, bears, or birds within protected or restricted areas. The workflow initiates with the collection of image or video data captured via surveillance mechanisms, including stationary cameras and drones.

Subsequently, this visual data undergoes several preprocessing steps such as resizing, normalization, and data augmentation, aimed at enhancing the model's ability to generalize across different scenarios and improving training stability. Once prepared, the data is fed into a deep learning model built upon Convolutional Neural Networks (CNNs).

The architecture comprises several convolutional layers activated by ReLU functions, along with max pooling operations that help extract key visual features like contours, textures, and shapes relevant to animal recognition. These extracted features are then flattened and passed through dense layers, allowing the model to form complex associations and high-level patterns critical for accurate classification.

The visual data collected is first subjected to preprocessing, which includes resizing the images to a standard dimension, applying normalization to maintain consistency in pixel intensity, and performing data augmentation to address variability in lighting conditions, animal posture, and environmental backgrounds. Following this, a Convolutional Neural Network (CNN) is employed to identify key visual traits such as contours, surface textures, and structural patterns that differentiate animal species. The network processes the data through sequential layers involving convolution operations, ReLU activations, and pooling mechanisms, which gradually distill the input into abstract and meaningful representations. These outputs are then flattened and fed into dense layers that perform the final classification..

D. *CNN Model*

Convolutional Neural Networks (CNNs) are a powerful deep learning framework utilized in the animal intrusion detection system to autonomously identify and extract relevant features from input images. Their layered structure allows for progressive analysis of visual patterns, making them highly effective for tasks involving image recognition. By applying optimized convolutional filters and kernels, CNNs can detect spatial hierarchies and learn discriminative characteristics essential for identifying various animals in surveillance footage.

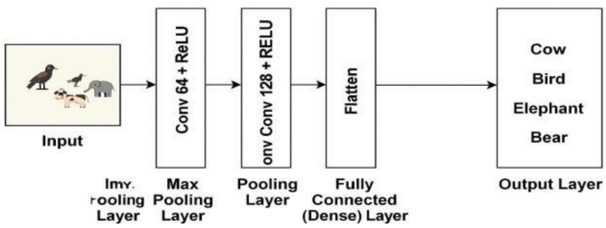

Figure 2: CNN architecture of the proposed method.

The designed CNN model for detecting animal intrusions is tailored to autonomously learn both spatial and contextual features from surveillance imagery. The architecture starts with an input layer that accepts standardized images—typically resized and normalized for consistency. Subsequent convolutional layers, activated by ReLU functions, are responsible for identifying localized patterns such as edges, textures, and contours. Each of these layers is coupled with max pooling layers to downsample the feature maps, retaining only the most essential characteristics and reducing computational complexity. Following the convolutional-pooling stages, the resulting features are flattened and fed into one or more dense layers, which help the network recognize complex relationships and high-level abstractions. The final classification is achieved through a softmax layer that assigns a probability score to each animal category (e.g., elephant, cow, bird, or bear). This architecture is engineered for reliable, real-time performance in diverse and dynamic outdoor conditions, making it an effective solution for applications in wildlife surveillance and security monitoring.

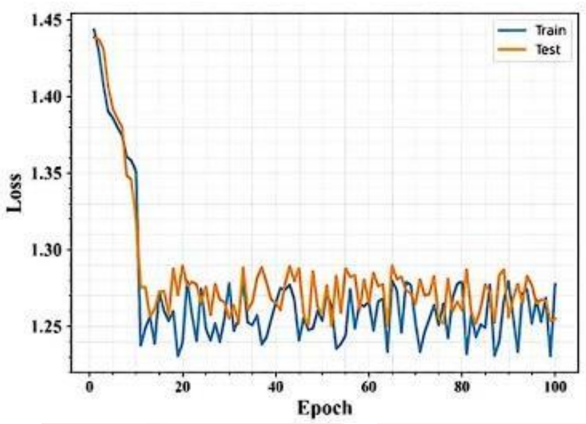

Figure 3: Accuracy Graph of CNN Model

E. YOLOV5 Model

YOLOv5 (You Only Look Once version 5) is a state-of-the-art object detection framework widely recognized for its exceptional speed and accuracy in real-time applications. Unlike conventional convolutional models that operate in sequential phases, YOLOv5 executes object detection in a single inference pass, which enhances efficiency—ideal for scenarios like animal intrusion monitoring. The model works by segmenting the input image into a grid and directly estimating class probabilities and bounding box coordinates from the image pixels, enabling it to identify multiple animals (e.g., cows, elephants, birds, or bears) simultaneously. The architecture of YOLOv5 is structured into three core segments: the Backbone, Neck, and Head. The Backbone (typically CSPDarknet) handles initial feature extraction; the Neck (using PANet or FPN structures) merges features across various scales to detect objects of different sizes; and the Head outputs class predictions along with bounding box data. Designed for flexibility and performance, YOLOv5 also supports transfer learning via pre-trained models and integrates techniques like mosaic augmentation, auto-anchor tuning, and dynamic input scaling to enhance generalization. These qualities make it a robust choice for real-time surveillance systems needing quick and accurate animal detection with minimal computational overhead.

F. Evaluation Parameters

To assess the performance of an animal intrusion detection model, several key evaluation parameters are used.

- **Accuracy**:
  Accuracy measures how many total predictions the model got right, including both actual intrusions and non-intrusions. It reflects the overall effectiveness of the model across all classes.

- **Precision**:
  Precision refers to the fraction of true animal intrusions among all instances the model predicted as intrusions. A high precision score suggests the system generates fewer incorrect alerts, enhancing its reliability in practical scenarios.

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

- **Recall:**
  Recall evaluates how effectively the model identifies true animal intrusions out of all actual intrusion events. A high recall indicates the model is good at capturing most of the real intrusion cases.

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **F1-Score**:
  The F1-score represents the harmonic average of precision and recall, offering a balanced assessment that considers both missed detections (false negatives) and incorrect alerts (false positives).

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **IoU (Intersection over Union)**:
  A crucial metric for object detection models such as YOLOv5, IoU assesses the overlap between the predicted bounding box and the actual ground truth box, with higher values indicating better localization accuracy.

- **mAP (mean Average Precision)**:
  Used to evaluate object detection performance, mAP calculates the average of precision scores across all detected classes (e.g., elephant, cow, bird). A higher mAP signifies more precise and consistent detections.

- **Confusion Matrix**:
  A structured table that displays true positives, false positives, false negatives, and true negatives for each class, providing detailed insight into the model's classification accuracy and error patterns.

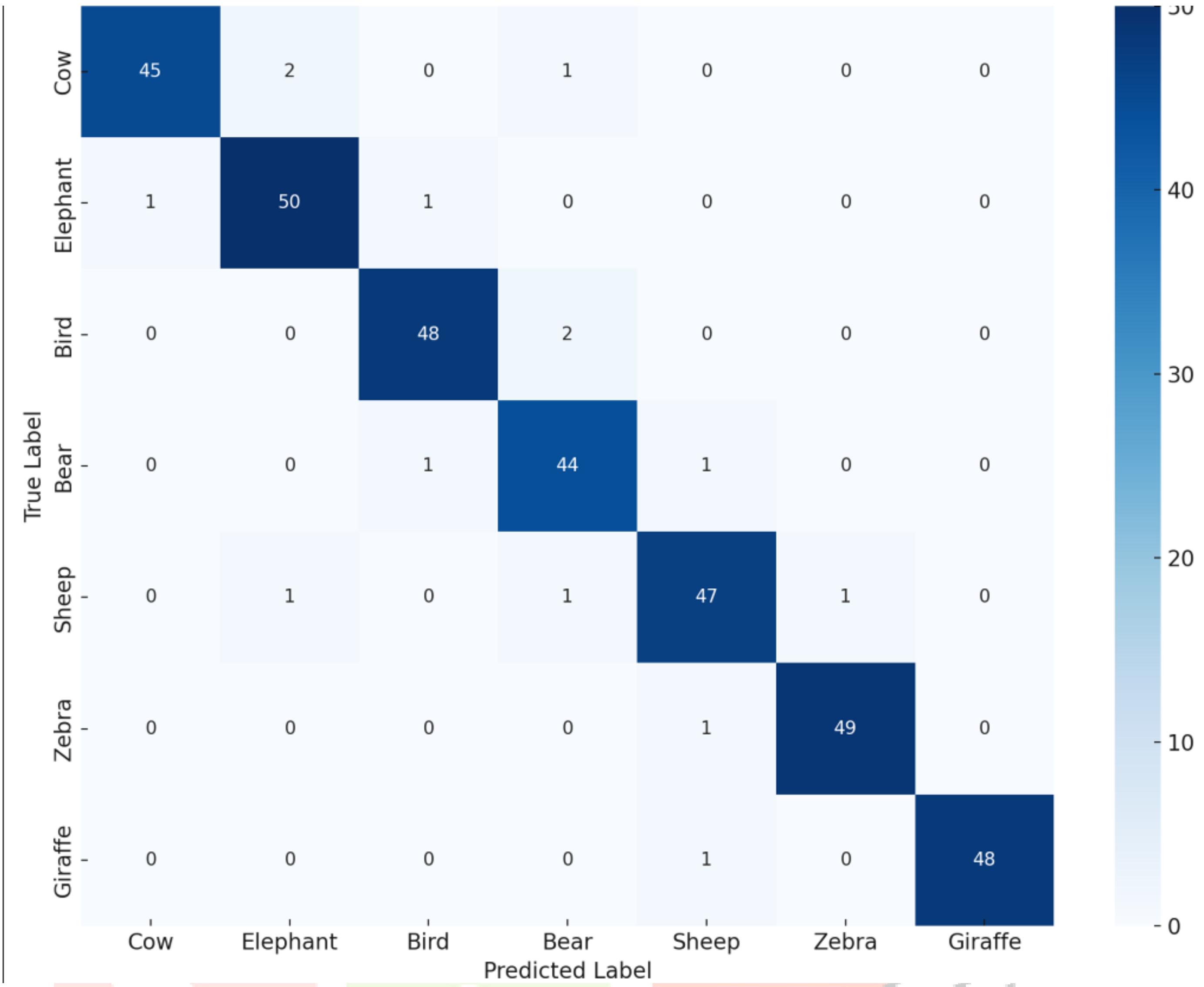

Figure 4: Confusion Matrix of CNN Model

IV. RESULTS AND DISCUSSION

In the implementation of animal intrusion detection, deep learning models such as CNN, YOLOv5, and VGG16 were evaluated using a curated animal dataset containing multiple classes including cow, elephant, zebra, giraffe, bird, bear, and sheep. The dataset was split into 80% training and 20% testing sets, ensuring proper model evaluation. Images were preprocessed through resizing (to 224×224 for YOLOv5 and VGG16, and 64×64 for CNN), normalization, and data augmentation techniques such as rotation, zoom, and flipping to enhance model robustness and generalization.

The CNN model showed decent accuracy and was faster to train due to its lightweight architecture, making it suitable for real-time applications with limited computational resources. However, it struggled slightly in differentiating animals with similar shapes or colors in cluttered environments.

The VGG16 model, known for its deep and uniform convolutional architecture, delivered higher classification accuracy and consistent detection performance across most animal categories. Its pre-trained weights significantly enhanced feature extraction, but it was computationally intensive and slower during training.

The YOLOv5 model achieved the highest accuracy and real-time performance. Its object detection capability with bounding boxes allowed precise localization of intruding animals, even in complex backgrounds. It effectively handled multiple animals in a single frame and maintained high precision and recall. Overall, YOLOv5 proved to be the most effective model for practical animal intrusion detection scenarios.

he proposed system was evaluated using three deep learning models—CNN, VGG16, and YOLOv5—to detect and classify different animals that may intrude into restricted or agricultural areas. The dataset included thousands of annotated images representing animals such as cow, elephant, zebra, giraffe, bird, bear, and sheep, captured in varied lighting, orientations, and natural environments to simulate real-world conditions.

All models underwent the same preprocessing pipeline, which included:

- Image resizing (64×64 for CNN, 224×224 for VGG16 and YOLOv5),
- Normalization to scale pixel values between 0 and 1,
- Data augmentation techniques such as random rotation, zoom, and horizontal flip to simulate different intrusion scenarios and enhance generalization.

Model Performance:

- CNN Model: Achieved satisfactory accuracy with low computational cost. It trained faster and required fewer resources, but its performance degraded when detecting small or partially occluded animals. The confusion matrix showed misclassifications especially between similar-looking animals (e.g., sheep vs. goat-like silhouettes).
- VGG16 Model: Showed improved accuracy and precision due to its deeper convolutional layers. It was particularly effective in feature extraction, leading to better detection of distant or camouflaged animals. However, due to its large number of parameters, it consumed more memory and had a longer training time.
- YOLOv5 Model: Delivered the best overall performance in terms of detection accuracy, real-time speed, and generalization. It could successfully identify multiple animals in a single frame with precise bounding boxes. Its precision-recall curve indicated robust detection even under challenging conditions such as night-time or partial visibility.

Evaluation Metrics:

- The models were compared using accuracy, precision, recall, F1-score, and mean Average Precision (mAP).
- YOLOv5 scored the highest in mAP (~92%), followed by VGG16 (~89%) and CNN (~85%).
- Confusion matrices revealed that YOLOv5 had the least false positives and false negatives, making it highly reliable for real-time surveillance.

In conclusion, while all models demonstrated potential for animal intrusion detection, YOLOv5 stands out as the most practical choice due to its balance of speed, accuracy, and robustness, making it suitable for deployment in real-time smart surveillance systems for farms and forest borders.

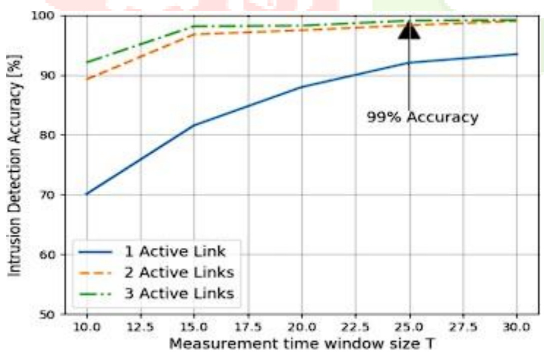

Figure 4: Accuracy Graph

CONCLUSION AND FUTURE SCOPE

This research explored the application of advanced deep learning models, including CNN and YOLOv5, for detecting animal intrusions in sensitive areas such as farmlands and forest borders. A diverse and well-labeled dataset of various animal species was employed, and preprocessing techniques such as resizing, normalization, and data augmentation were used to enhance model performance across varied environmental conditions. Among the models tested, YOLOv5 outperformed others in terms of real-time detection speed and accuracy, while VGG16 offered reliable results through deeper feature extraction. Though CNN proved to be lightweight and quick to train, it was slightly less accurate in complex visual scenarios. The models were assessed using several performance metrics including accuracy, precision, recall, F1-score, mAP, and confusion matrices to provide a comprehensive evaluation. The findings confirm that deep learning techniques—especially YOLOv5—are highly effective for animal detection in real-world applications, with potential benefits in minimizing crop losses and human-wildlife interactions. Looking ahead, the system could be further improved by integrating it with IoT-enabled devices and edge computing to deliver real-time alerts and automatic deterrence mechanisms. Adding support for thermal and night vision imaging, along with expanding the dataset to include more animal categories and real-time video streams, would enhance its practical utility. Such enhancements could make the system more adaptive and scalable for broader deployment in agricultural and wildlife monitoring settings.

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