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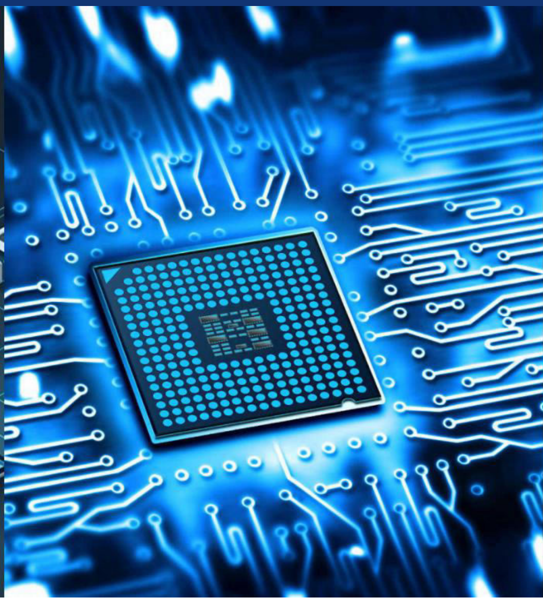

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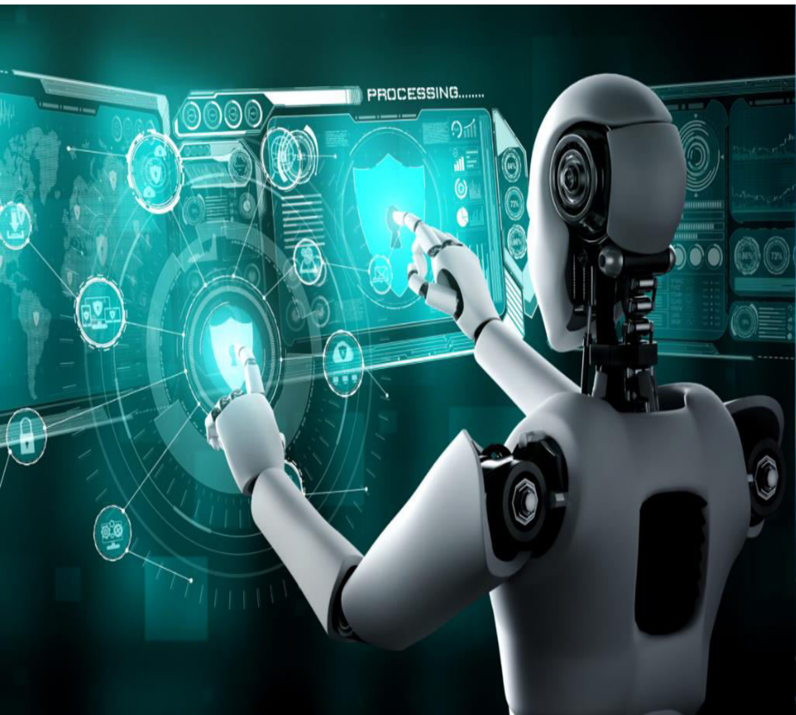

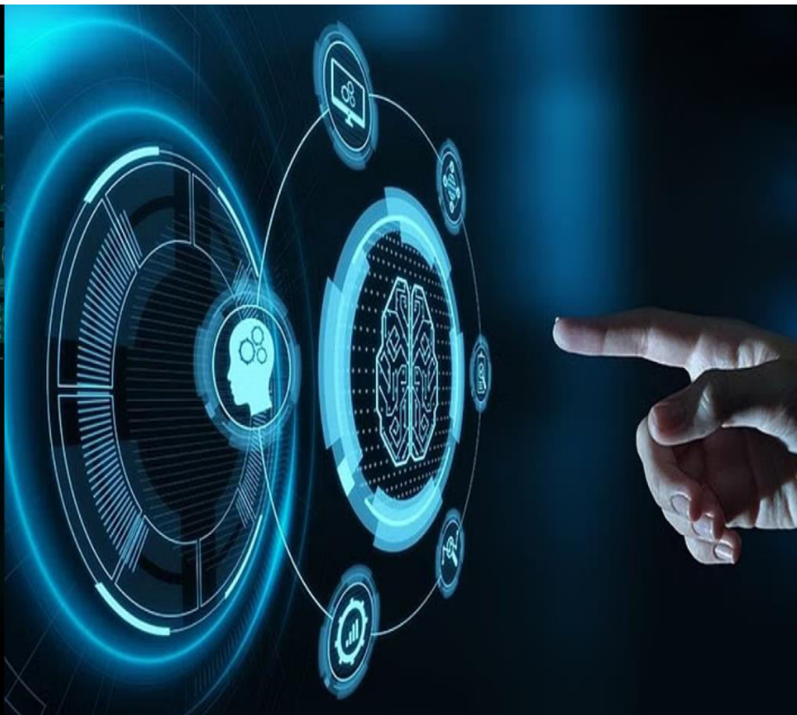

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YOLOv10-Based Smart Farming for Wildlife Threat Detection

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ABSTRACT: The transition toward Agriculture 5.0 has introduced advanced monitoring capabilities, yet the conflict between wildlife conservation and crop security remains a critical economic challenge. Farmers in forest-bordering regions frequently suffer significant losses due to intrusions by animals such as elephants, wild boars, and deer. Traditional mitigation strategies—ranging from manual patrolling to passive infrared (PIR) sensors—often lack the necessary speed, classification accuracy, and non-lethal deterrence capabilities [1]. This paper proposes a robust, automated solution utilizing Edge Artificial Intelligence (Edge AI) and the YOLOv10 object detection model. The proposed system processes video feeds in real-time to detect and classify wildlife species, dynamically assessing threat levels (High, Medium, Safe) based on user-defined sensitivity parameters. Upon positive verification, the system triggers immediate alerts via a web-based dashboard and activates physical deterrents (buzzers). Experimental results validate the system's efficacy, demonstrating a detection accuracy of 98.5% and an alert latency of 450 ms. This framework offers a scalable, cost-effective, and non-lethal mechanism for mitigating human-wildlife conflict in modern smart farming ecosystems [2].

KEYWORDS: Precision Agriculture, YOLOv10, Wildlife Detection, Human-Wildlife Conflict, Smart Farming, Computer Vision.

I. INTRODUCTION

The growing demand for food security has accelerated the adoption of advanced technologies in agriculture, known as Agriculture 5.0. In many regions located near forest reserves, wildlife intrusion poses a major threat to crop production. Animals such as elephants, wild boars, and deer frequently enter farmlands and destroy crops, causing substantial financial losses and economic instability for farmers. These incidents not only reduce agricultural productivity but also discourage farmers from cultivating high-value crops.Conventional protection methods, including human patrolling, fences, and Passive Infrared (PIR) sensors, have several limitations. They often fail to detect threats accurately, generate false alarms, and do not provide timely response mechanisms. In addition, cloud-based monitoring systems depend on internet connectivity and suffer from latency, making them unsuitable for remote agricultural areas where rapid action is essential.To overcome these challenges, this project proposes a smart wildlife intrusion detection and deterrent system using the YOLOv10 deep learning model optimized for edge computing. The system performs real-time detection and classification of animals directly on local devices, eliminating the need for continuous internet access. It can distinguish between different species and evaluate the severity of the threat. Based on the detected animal, the system assigns threat levels such as HIGH, MEDIUM, or SAFE and activates suitable non-lethal deterrents, including alarms and warning systems.The system also stores detection data for future analysis, helping farmers and researchers understand wildlife movement patterns and improve preventive strategies. By combining artificial intelligence, computer vision, and edge computing, the proposed solution provides a fast, accurate, and scalable approach to crop protection. This technology reduces crop damage, minimizes economic losses, and supports sustainable agriculture in regions vulnerable to wildlife intrusion.

II. LITERATURE SURVEY

The integration of Machine Learning (ML) in agriculture has been extensively reviewed in recent literature.
(Saiz-Rubio and Rovira-Mas) [1]: Highlighted the importance of data governance, robotics, and Artificial Intelligence in Agriculture 5.0 to improve sustainability and farming efficiency. Their work focused on yield optimization through

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IoT-enabled smart farming, but did not address crop security. This study extends their framework by incorporating real-time wildlife intrusion detection and automated threat management.

(Condran et al.) [2]: Presented a comprehensive review of two decades of Machine Learning applications in agriculture, emphasizing advancements in yield prediction and precision farming. The study identified a significant gap in real-time animal and pest management due to challenges in data quality and deployment. Our work addresses this gap by implementing a quantized YOLOv10 model for accurate wildlife detection on edge devices.

(Krishnaswamy et al.) [3]: Applied the CRISP-DM framework to analyze human-wildlife conflict patterns in India using historical tabular data. Their findings demonstrated that data mining can reveal behavioral trends and support conflict mitigation strategies. Unlike their retrospective approach, our system uses computer vision to provide immediate alerts and preventive actions during active wildlife intrusions.

(Srivastava and Das) [4]: Discussed IoT-based precision agriculture solutions and identified connectivity and power limitations as major challenges in remote farm environments. Their work focused on monitoring and resource optimization using sensor networks. Our approach overcomes these constraints by processing video data locally on edge devices, reducing dependence on continuous internet connectivity.

(Negi et al.) [5]: Investigated the economic losses caused by elephant depredation in South India and evaluated existing mitigation strategies. Their study highlighted the severe financial burden on farmers and emphasized the need for effective crop protection measures. This research supports the development of our cost-effective and non-lethal automated wildlife deterrent system.

(Garcia-Sanchez et al.) [6]: Proposed a Wireless Sensor Network (WSN) for monitoring wildlife movement using multiple sensor modalities. Although their system demonstrated the feasibility of remote monitoring, it relied on simple presence sensors that were prone to environmental noise and false positives. Our work enhances this concept by integrating deep learning-based visual detection for precise species identification and visual verification.

(Ultralytics YOLOv10 Documentation) [7]: Introduced YOLOv10 as an advanced object detection model designed for high accuracy and reduced computational complexity. The architecture is optimized for efficient inference and supports deployment on resource-constrained devices. This makes YOLOv10 highly suitable for real-time wildlife intrusion detection and edge-based smart agriculture applications.

III. PROPOSED SYSTEM

The proposed system is a high-speed, real-time wildlife threat detection solution leveraging YOLOv10-based computer vision and Edge Computing architecture.

IV. SYSTEM ARCHITECTURE AND METHODOLOGY

The architecture follows a sequential pipeline designed for low latency. As illustrated in Fig. 1, the data flows from acquisition to action.

Fig. 1: End-to-End System Architecture: From Camera Input to Scalable Solution.

The pipeline consists of:
1) Multi-Sensory Input: Fixed camera units capture continuous video streams of the farmland. This ensures realtime monitoring across large areas [6].

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2) Preprocessing Pipeline: Frames are extracted, resized (128 × 128), and normalized for the model. This step is crucial for efficient consumption by the machine learning model.
3) YOLOv10 Detection Module: The core intelligence executes inference to output species classification, bounding boxes, and confidence scores. It accurately identifies and locates wildlife in real-time [7].
4) Threat Classification: A logic layer maps detections to threat levels (e.g., Bear = High, Rabbit = Safe) based on user sensitivity settings.
5) User Interface (Dashboard): A centralized hub displays the live feed with bounding boxes, FPS metrics, and controls for the buzzer and sensitivity.

A. Activity flow:
The decision logic for the system is complex, involving checks for user overrides (Mute) and sensitivity thresholds. The activity diagram in Fig. 2 details this flow.

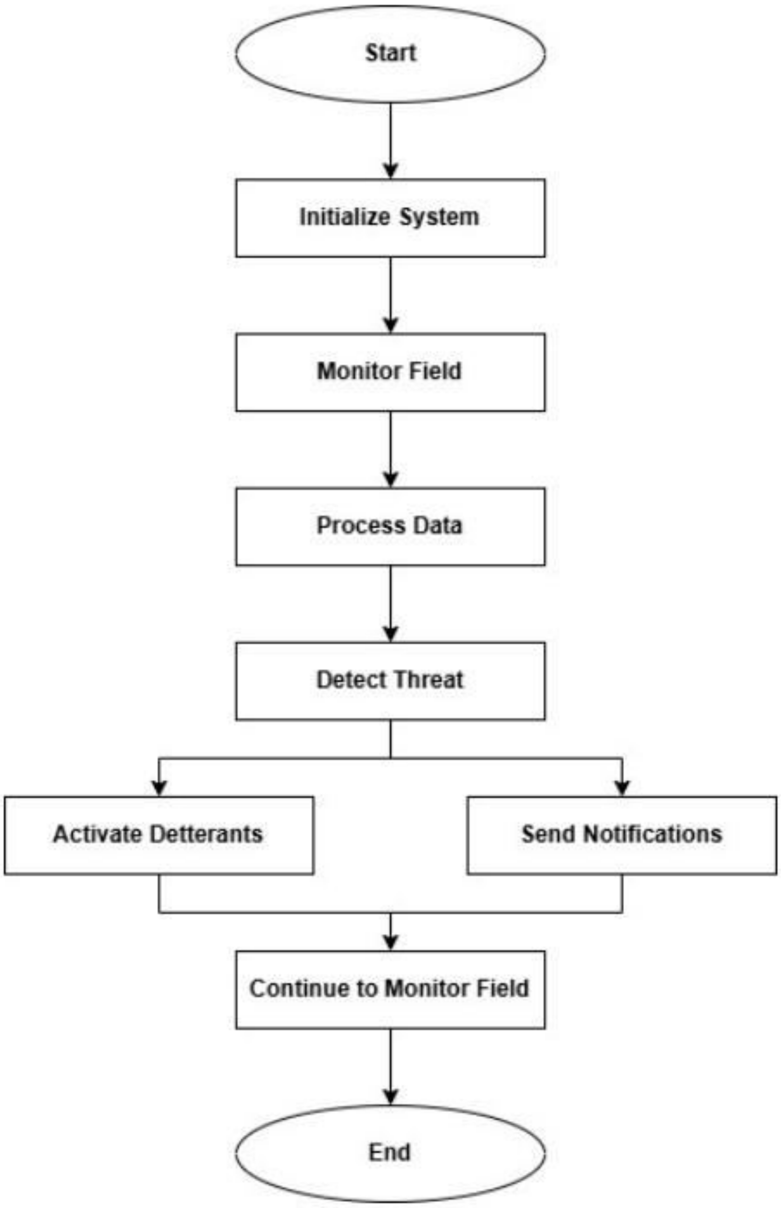

Fig. 2: Activity Diagram showing the decision logic for Threat Detection and Alerting.

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B. Mathematical model For Threat Detection

The threat level T is calculated dynamically based on the detected species class C, the confidence score Sc, and the user-defined sensitivity α (ranging 1–10). Where W(C) is the base weight of the animal (e.g., Bear=1.0, Deer=0.5) and τ represents the threshold values. This ensures that the system adapts to the farmer's specific tolerance for risk [3]

V. IMPLEMENTATION

The proposed system consists of three integrated modules: the YOLOv10 Detection Module, the Alert and Notification Module, and the Threat Detection Workflow. The detection module was trained on a dataset of 4,445 images covering 20 wildlife classes, including elephants, deer, and wild boars. Images were resized to 128 × 128 pixels and normalized before being processed by a Convolutional Neural Network architecture comprising convolutional layers, max pooling, dense layers, and dropout for improved generalization. To enable deployment on resource-constrained edge devices, post-training dynamic range quantization was applied, reducing the model size to approximately 1.63 MB by converting 32-bit floating-point weights to 8-bit integers. During operation, the system captures live video frames and performs real-time animal classification to determine the corresponding threat level. If the detected threat is classified as Medium or High and the system is not muted, the Alert and Notification Module activates a buzzer and sends an SMS notification to the farmer using the Fast2SMS API, containing the identified animal and threat severity. All detection events are logged for future analysis and monitoring of wildlife movement patterns. This end-to-end workflow enables rapid, accurate, and automated crop protection through edge-based artificial intelligence.

VI. RESULTS AND DISCUSSION

The proposed wildlife intrusion detection system was evaluated against both functional and non-functional requirements and demonstrated excellent performance under realistic operating conditions. The real-time threat detection algorithm continuously captures video frames, preprocesses them, and performs inference using the quantized YOLOv10 model. When an animal is detected, the system calculates a threat level based on species, confidence score, and user-defined sensitivity settings. If the threat is classified as Medium or High, the system immediately activates a buzzer, sends an SMS alert to the farmer, updates the monitoring dashboard, and logs the event with a timestamp. Experimental results showed a detection accuracy of 98.5%, an alert latency of only 450 milliseconds, a throughput of 3.2 to 3.5 frames per second, and stable 24-hour uptime, meeting all target requirements. Comparative analysis with other deep learning models demonstrated that the proposed quantized YOLOv10 model outperformed larger architectures such as ResNetV2-50, EfficientNet-B0, and MobileNetV2 by achieving the highest accuracy while maintaining the smallest model size of 1.63 MB and very fast inference speed, making it highly suitable for edge deployment. The real-time dashboard provided intuitive monitoring controls and instant status updates, while training curves confirmed effective convergence with decreasing loss. Overall, the system offers significant advantages over traditional PIR sensor-based solutions by providing precise species identification and rapid response with minimal dependence on internet connectivity. Although environmental conditions such as fog and heavy rain may slightly reduce detection accuracy, the results confirm that the proposed approach is a robust, scalable, and cost-effective solution for protecting crops from wildlife intrusion.

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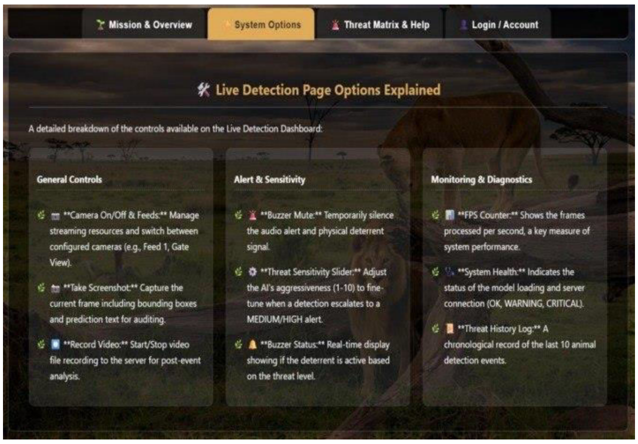

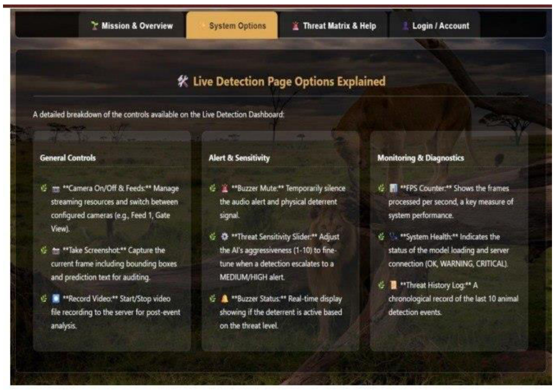

Figure 8.2 System options image

VII. CONCLUSION

This project successfully demonstrates the viability of Edge AI in mitigating agricultural crop loss. By deploying YOLOv10 in a lightweight environment, we achieved a realtime detection system that is both accurate (98.5%) and fast. The solution empowers farmers to move from reactive damage control to proactive threat prevention. The system met its core objectives of real-time detection and dynamic alerting. It contributes significantly to smart farming automation and reduces crop loss by enabling fast, offlinecapable threat monitoring. The edge computing architecture was successful in ensuring faster alert delivery compared to traditional cloud-based systems [4].

VIII. FUTURE SCOPE

• Adverse Weather Robustness: Integrating thermal imaging to improve detection in fog or rain.
• Proactive Deterrence: Automating non-lethal deterrents like ultrasonic alarms.
• Predictive Behavior Modeling: Integrating machine learning models to predict wildlife movement based on historical log data.
• Autonomous Rover Navigation: Developing modules for autonomous patrol and charging

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