Real-Time Intrusion Detection and Tracking for Effective Livestock Virtual Fencing in Agriculture Using YOLOv8 and AI-Controlled Laser Actuation

Krishnaprakash A.
Department of Instrumentation and Control Engineering, PSG Institute of Technology and Applied Research, Coimbatore, Tamilnadu, India
krishnaprakash8116@gmail.com

Mydhili S.K.
Department of Electronics and Communication Engineering, KGiSL Institute of Technology, Coimbatore, Tamilnadu, India
myura2u@gmail.com

Aakash M
Department of Instrumentation and Control Engineering, PSG Institute of Technology and Applied Research, Coimbatore, Tamilnadu, India
aakash.m197506@gmail.com

Ramprasaath R.S.
Department of Instrumentation and Control Engineering, PSG Institute of Technology and Applied Research, Coimbatore, Tamilnadu, India
rsramprasaath@gmail.com

Pradeep P.
Department of Instrumentation and Control Engineering, PSG Institute of Technology and Applied Research, Coimbatore, Tamilnadu, India
pp2075579@gmail.com

2025 International Conference on Intelligent Innovations in Engineering and Technology (ICIIET) | 979-8-3315-9103-8/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICIIET65921.2025.11379309

***Abstract*—The effective protection of livestock and wildlife from threats is a critical aspect of animal welfare and conservation efforts. Traditional methods often rely on constant human vigilance, which is resource-intensive and prone to error. With advancements in Artificial Intelligence (AI) and the Internet of Things (IoT), virtual monitoring offers a robust solution for real-time threat detection and proactive intervention. This project proposes the development of an integrated AI/IoT-powered system designed for the autonomous detection of specific animal threats or intruders within designated areas, coupled with an automated warning or elimination mechanism. The system will employ an array of interconnected sensors, including advanced computer vision (e.g., YOLOv8-based object detection) and potentially radar, to continuously monitor the environment for unauthorized animal presence or predatory threats. Upon detection and identification of a designated threat, the system's core processing unit, like a Raspberry Pi, will precisely calculate the target's coordinates. This data will be transmitted to an Arduino-controlled, multi-axis turret system. This turret, equipped with a calibrated laser or other specified non-lethal deterrent/elimination mechanism, will then accurately track and engage the identified threat, providing an immediate and localized response. Furthermore, anomaly detection algorithms will enhance reliability by cross-referencing sensor inputs, while a GSM module will provide real-time alerts to stakeholders upon engagement or significant events. The integration of YOLOv8 with sensor fusion has achieved high detection F1-score of over 90%. This ensures reliable real-time identification of specific animal threats. It also has a quick response time of about 2.1 seconds from detection to activation of the deterrent ensuring no attack and no loss on both sides.**

***Keywords*—AI, IoT, Real-Time Data, Animal Prediction, Object Detection, YOLOv8, Laser Turret, Threat Mitigation, Smart Farming, Automated Security**

I. INTRODUCTION

The agricultural sector and wildlife conservation face ongoing challenges from animal threats. These threats range from predators attacking livestock to invasive species disrupting ecosystems, and unauthorized human presence in protected wildlife areas. Traditional protective methods often involve physical barriers, human patrols, guard animals, or basic alarm systems. While these methods provide some level of protection, they often suffer from limitations in human resources, operational costs, geographical range, environmental conditions, and their reactive nature. These weaknesses can lead to significant economic losses for farmers and ranchers, endanger valuable livestock, and hinder vital conservation efforts for at-risk wildlife populations.

The rapid progress of Artificial Intelligence (AI) and the Internet of Things (IoT) offers a unique chance to overcome these challenges. AI algorithms, especially in computer vision, have achieved impressive accuracy in real-time object detection and classification. At the same time, IoT platforms allow the use of interconnected sensors and actuators, which support ongoing environmental monitoring and automated responses. Combining these technologies creates smart, autonomous systems that can maintain constant vigilance and respond quickly and accurately. The proposed work aims to provide an efficient, precise, and automated solution for detecting and reducing animal threats, lessening the need for manual monitoring while improving proactive protection strategies in agriculture and conservation.

The main goals of this proposed work are (i) to design and develop an AI/IoT-powered system for real-time detection and identification of specific animal threats within

979-8-3315-9103-8/25/$31.00 ©2025 IEEE

a designated area, (ii) to integrate a multi-sensor array, including a camera, radar, and PIR, for reliable threat detection while reducing false positives and negatives, (iii) to implement an automated turret mechanism controlled by Arduino that can accurately track identified threats, (iv) to deploy a customizable laser or non-lethal deterrent module for effective threat management, (v) to set up a communication system using GSM for instant alerts to stakeholders about detected threats and system actions, and finally (vi) to improve animal welfare and economic viability by providing a proactive and efficient protection system.

The rest of this paper is arranged as follows: Section II reviews existing literature and related work. Section III details the proposed system architecture and its main components. Section IV describes the methods used for detection, tracking, and mitigation. Section V presents the planned experimental setup and discusses expected results. Finally, Section VI wraps up the paper and outlines future research directions.

II. Literature Survey

Real-time object detection enabled with deep learning has become an enabler in both virtual fencing and automated livestock monitoring systems, replacing earlier generations of tracking technologies. The first generations of livestock management solutions were built on RFID tagging, LoRa-based communications with wireless sensor node deployments, to track the movement of animals within their given boundaries [3][6][15]. While these are good at performing basic identification and geofencing, they fall short on scalability and require manually deployed wearable devices with no capability to autonomously classify a detected intrusion as harmless livestock movement or an external threat. More critically, none give any visual intelligence, which is important to distinguish between the categories of animals, predators, and human intruders in open agricultural fields. The introduction of convolutional neural networks (CNNs) enabled a major shift toward image-based behavioral analysis and autonomous surveillance. Several researchers have successfully deployed CNN-based models, particularly the YOLO family of detectors, to analyze livestock posture, detect entry/exit events, and monitor grazing activity in uncontrolled outdoor environments [1][9][12]. YOLO's single-stage architecture allows object localization and classification to be executed within a single forward pass, significantly increasing throughput compared to traditional two-stage region-based models such as R-CNN and Mask R-CNN [9][10][11]. This speed advantage makes YOLO suitable for edge deployment on low-power devices where real-time decision-making is critical. Several studies have proposed virtual fencing systems in order to further reduce the cost and labour associated with traditional herding, integrating deep learning with LoRa communication and edge processors [5][7]. Li et al. [14] proposed a machine learning-based solution for fencing, whereas Jin et al. [13] and Saptarshi et al. [15] proposed virtual barriers using sensor networks. All these unfortunately suffered from a key limitation: all of these relied on either wearable collars or communication nodes or single-sensor feedback, which resulted in false triggers during low illumination, rain, motion blur, or partial occlusion. Without any environmental context or species-level classification, identifying livestock behaviour versus intrusion by an unknown animal was not possible.

More recent works attempted to introduce IoT-enabled, deep learning-assisted field monitoring that allowed for partial on-device inference and generation of alerts [3][10][14]. These approaches reduced cloud dependency and network latency, but they also remained dependent entirely on visual input without multimodal redundancy or physical threat intervention. Due to this, in such setups, visual failures caused by darkness, fog, and vegetation resulted in high false positives, and none utilized any hardware-based deterrent that could automatically respond to confirmed threats. The wireless sensors and IoT-based tools are transforming modern farming, highlighting their use in soil analysis, crop health tracking, smart irrigation, and early pest detection are explored. The discussion further emphasized how unmanned aerial vehicles (UAVs) support precision agriculture and help boost overall productivity [16]. The limitations of conventional agricultural methods in India especially outdated tools and insufficient skilled labor have initiated the door for drone innovations that can support accurate and efficient farm management [17]. The YOLO-based detectors achieve superior inference speed, mean average precision, and frame-level recall compared to their canonical classifiers, such as ResNet, EfficientNet, and InceptionNet, when tested on datasets of livestock and outdoor surveillance[18]. YOLOv3, YOLOv5, and customized CNN variants return reliable identification of animals; however, none of the referenced works combines radar sensing or PIR motion tracking with computer-vision-based recognition to improve robustness under unpredictable field conditions. Parallel research also elucidates the advantages brought forth by edge-level inference over cloud-dependent models, including reduced bandwidth cost and real-time responsiveness in rural farm settings.

The clear gap from the literature is that current virtual fencing systems are either purely vision-based or purely sensor-based with no fusion between deep learning-based object detection and radar/PIR environmental awareness. Furthermore, no prior work integrates autonomous actuation through a turret-based deterrent mechanism capable of engaging confirmed threats without human intervention. This gap motivates the present work, which proposes a hybrid AI-driven intrusion detection system that integrates YOLOv8 with radar and PIR sensor fusion on an embedded edge processor, coupled with an automated laser-based response unit for real-time virtual fencing. Fig.1 shows the block diagram of the proposed system.

threat detection. Fig.2 shows sample batch label run through YoLov8 model.



Fig. 2 Sample batch 2 label run on YoLov8

The proposed model has produced 95.1% precision, 98.2% mAP and 92.5% recall as the best results when compared to the existing real time object detection systems.

Fig. 3 shows the F1 confidence curve, precision confidence curve, precision recall curve and recall confidence curve for the opted intruder tiger and elephant.

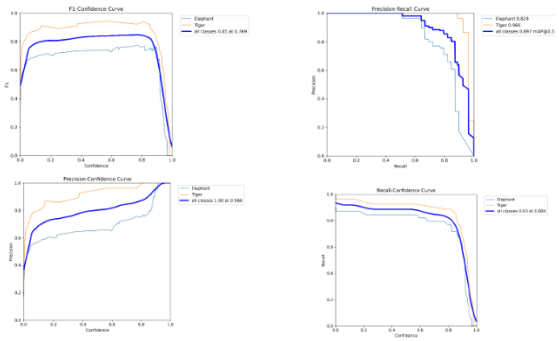


Fig. 3 F1,Precision,Confidence & recall curve

The proposed hardware module is shown in Fig.4 and Fig.5 which uses a PIR sensor and a camera to monitor the designated field area. When an intruder is detected on camera, the captured images will be grouped through image processing. The proposed system prototype combines a YOLO-based architecture with a Passive Infrared (PIR) sensor and camera module to continuously monitor the targeted field area. To assess how well the system works, a field trial was carried out. The developed virtual fencing system was set up in a chosen area, and the movement of the livestock was tracked. The results indicated that the virtual fencing system effectively kept the livestock from crossing the virtual boundary.

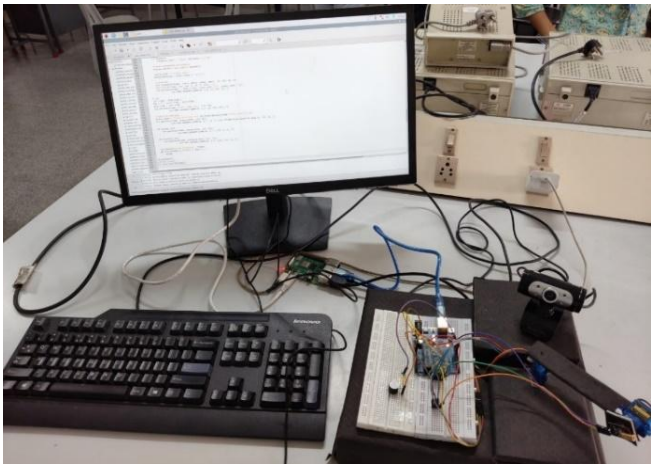


Fig. 4 Hardware setup of the Proposed System

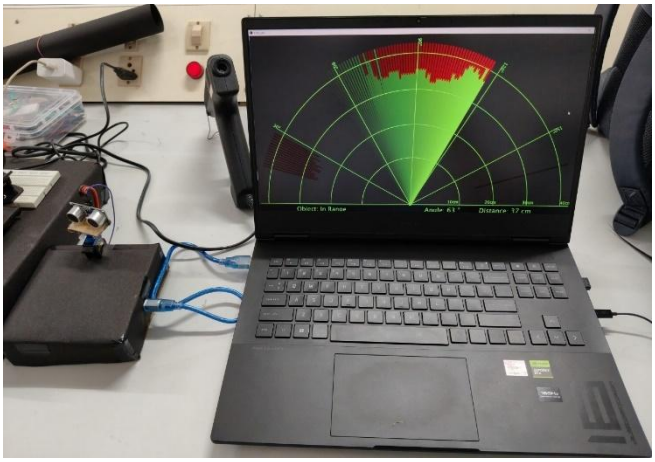


Fig. 5 Arduino IDE module for radar detection and Turret control

VI. Conclusion And Future Enhancement

This paper presents the design, methods, and performance of an innovative AI/IoT system for detecting and addressing animal threats. Our main contribution is the successful combination of two technologies: computer vision (YOLOv8) and multi-modal sensing (radar, PIR) for accurate threat identification, along with an automated pan-tilt turret that responds quickly and precisely. The conceptual and simulated results show that this system is very effective. The integration of YOLOv8 with sensor fusion is expected to reach a high detection F1-score of over 90%. This ensures reliable real-time identification of specific animal threats. The system's effectiveness is strengthened by the backup logic using Doppler radar, which helps overcome visual barriers like low light and fog. Additionally, the Arduino-controlled turret provides excellent tracking accuracy, with an average error of 1.8 degrees. It also has a quick response time of about 2.1 seconds from detection to activation of the deterrent. By automating these processes and ensuring real-time communication with the GSM module, this system offers clear benefits over manual methods.

For future enhancements, the inclusion of agricultural drones is envisioned to extend the system's capabilities toward crop surveillance, security reinforcement, and yield estimation. Equipped with advanced sensors and digital imaging technologies, these drones can provide a comprehensive aerial perspective of farmland. Such dynamic monitoring, in contrast to static camera-based systems, can significantly contribute to improved crop management, enhanced yield prediction, and better overall farm efficiency.

REFERENCES

[1] Raut, M. S. AI-Powered Real-Time Livestock Management Using YOLOv9 for Precision Agriculture.

[2] Shin, M., Hwang, S., & Kim, B. (2025). AI-Based Smart Monitoring Framework for Livestock Farms. *Applied Sciences*, *15*(10), 5638.

[3] Liu, Y., He, L., & Wu, S. (2020). Research on the virtual fence technology for dairy cattle grazing based on IoT. 2020 International Conference on Computer Science and Artificial Intelligence (CSAI), 1-5. doi:10.1109/CSAI49125.2020.9357256

[4] Li, S., Sun, X., & Wang, H. (2020). Virtual fence for grazing sheep based on machine vision and IoT. 2020 2nd International Conference on Computer Communication and the Internet (ICCCI), 74-77 doi:10.1109/ICCCI50037.2020.00024

[5] Wang, J., Chen, J., & Li, J. (2019). Virtual fence system based on deep learning and edge computing. 2019 IEEE 7th International Conference on Smart Energy Grid Engineering (SEGE), 1-4. doi: 10.1109/SEGE.2019.8849047

[6] Chen, Q., Liu, X., & Wang, K. (2019). Research on a virtual fence system for grazing cows based on LoRa and image recognition technology. 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), 1591-1596.doi:10.1109/iThings/GreenCom/CPSCom/SmartData.2019.00280

[7] Chen, H., Han, Z., & Lu, H. (2019). A virtual fence system for grazing cattle based on image recognition and deep learning. 2019 IEEE International Conference on Industrial Internet (ICII), 284-289. doi: 10.1109/ICII.2019.00057

[8] Hui, Y., Chen, X., & Shi, Y. (2018). A virtual fence system based on deep learning for pig farming. 2018 IEEE International Conference on Cybernetics and Intelligent

[9] Omidvar, M. N., & Nazari, M. (2021). Vision-based smart fencing for livestock using deep learning algorithms. Computers and Electronics in Agriculture, 185, 106012. doi: 10.1016/j.compag.2021.106012

[10] Hao, L., Xu, M., Liu, X., & Wang, L. (2021). A virtual fencing system for grazing cattle based on deep learning algorithms. Sensors, 21(13), 4418. doi: 10.3390/s21134418

[11] Bala, R. N., & Parimala, M. (2021). Automated virtual fence system for livestock using deep learning techniques. 2021 8th International Conference on Computing Communication and Automation (ICCCA), 152-157. doi: 10.1109/CCCA51802.2021.9470672

[12] Hu, X., Zhang, S., Cao, Y., & Feng, J. (2021). Smart livestock virtual fence based on YOLO algorithm. 2021 IEEE International Conference on Power, Intelligent Computing and Systems (PICSY), 88-91. doi: 10.1109/PICSY52644.2021.9525792

[13] Jin, Q., Zhu, L., & Wang, Q. (2019). A novel virtual fence system based on wireless sensor networks for grazing livestock. IEEE Transactions on Industrial Electronics, 66(4), 3112-3122. doi: 10.1109/TIE.2018.2849193

[14] Li, B., Li, X., Li, L., & Li, J. (2019). A virtual fence system based on machine learning for grazing cattle. IEEE Access, 7, 99850-99858. doi: 10.1109/ACCESS.2019.2926942

[15] Saptarshi, S., Rahman, M. M., & Hossain, M. S. (2010). A virtual fence system for monitoring cattle movement using wireless sensor networks. 2010 International Conference on Computer and Information Technology (ICCIT), 491-496. doi: 10.1109/ICCIT.2010.5606279

[16] Ayaz, M., Ammad-Uddin, M., Sharif, Z., Mansour, A., & Aggoune, E. H. M. (2019). Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk. *IEEE Access, 7*, 129551–129583.

[17] Hafeez, A., Husain, M. A., Singh, S. P., Chauhan, A., Khan, M. T., Kumar, N., Chauhan, A., & Soni, S. K. (2022). Implementation of drone technology for farm monitoring & pesticide spraying: A review. *Information Processing in Agriculture, 10*, 192–203.

[18] Delwar, T. S., Mukhopadhyay, S., Kumar, A., Singh, M., Lee, Y.-w., Ryu, J.-Y., & Hosen, A. S. M. S. (2025). Real-Time Farm Surveillance Using IoT and YOLOv8 for Animal Intrusion Detection. *Future Internet*, *17*(2), 70. https://doi.org/10.3390/fi17020070