Journal Homepage: www. ijarpr.com ISSN: 3049-0103 (Online)

International Journal of Advance Research Publication and Reviews

Vol 02, Issue 10, pp 249-257, October 2025

Low-Power Edge ML-Driven Ultrasonic Deterrent System for Safeguarding Crops from Wild Animal Intrusion

Abhijeet R. Thakur[1], Ankit Navgeet Joshi[2]

Research Scholar[1], M Tech Supervisor[2]
[1,2]Department of Computer Technology & Applications, School of Engineering Shri Satya Sai University and Medical Sciences, Sehore (M.P)
abhijeet.thakur@icloud.com

ABSTRACT:

Wild animal intrusion remains a major challenge for farmers, leading to significant crop losses and reduced agricultural productivity. Conventional deterrent techniques, such as fencing, chemical repellents, or manual guarding, are often costly, labor-intensive, and environmentally unsustainable. To address this issue, this work proposes a low-power EdgeML-driven ultrasonic deterrent system designed to safeguard crops against wild animal intrusions. The system leverages edge machine learning (EdgeML) to enable real-time detection and classification of animal movement near farmland while operating efficiently on resource-constrained hardware. Ultrasonic sound waves, which are non-lethal and eco-friendly, are selectively triggered to deter animals without causing harm to humans or livestock. By integrating low-power sensors, edge computing modules, and adaptive ML models, the proposed solution ensures continuous operation in remote agricultural areas with minimal energy requirements. Experimental results demonstrate that the system provides high detection accuracy, reduced false alarms, and reliable deterrence effectiveness, making it a sustainable and cost-effective approach for modern precision agriculture.

Keywords: Edge Machine Learning (EdgeML), Low-power system, Ultrasonic deterrent, Wild animal intrusion, Crop protection, Precision agriculture, Edge computing, Sustainable farming

Introduction

Agriculture has always been the backbone of human civilization and continues to be the primary source of food, livelihood, and economic development for billions of people across the world. Farmers work tirelessly to ensure that crops are nurtured, maintained, and harvested to feed growing populations. However, agriculture constantly faces various challenges including pests, diseases, climatic variations, and wild animal intrusions that cause significant crop damage. Among these challenges, wild animal intrusion remains one of the most pressing issues, particularly in rural and forest-adjacent agricultural zones[1][2]. Animals such as wild boars, deer, elephants, monkeys, and other herbivores often enter farmlands in search of food and water, leading to massive destruction of standing crops. This not only reduces yield but also causes financial stress for farmers who depend entirely on seasonal harvests. Farmers in many regions adopt manual guarding methods to protect their farms, but such practices are labor-intensive, exhausting, and often impractical at night or over large fields. Physical barriers like fencing are another commonly used method, yet they are expensive to install, require constant maintenance, and in some cases can even be harmful to animals[3-7]. Chemical repellents pose further problems since they may affect soil fertility, crop quality, and environmental safety. Traditional scare tactics like using sound or light devices may initially work but animals eventually adapt to them, reducing their long-term effectiveness. Hence, there is a clear demand for sustainable, intelligent, and cost-effective solutions that can safeguard crops without harming the ecosystem. With rapid advancements in digital technologies, smart farming approaches have emerged as a promising direction for addressing such challenges. Precision agriculture techniques now integrate sensors, communication systems, and intelligent decision-making models to protect crops while optimizing available resources. Among these, machine learning and artificial intelligence have become powerful tools for real-time detection and prediction of threats in agriculture[8]. However, running conventional ML or AI models requires large computing power and stable internet connectivity, which may not always be feasible in remote farmlands. This limitation has motivated the rise of Edge Machine Learning (EdgeML), where models are deployed directly on edge devices with limited computational power. EdgeML enables local data processing, reducing the dependency on cloud servers and ensuring real-time response even in areas with poor network infrastructure[9] Moreover, it reduces latency, lowers energy consumption, and enhances privacy since sensitive data need not always be transmitted externally. The integration of EdgeML in agricultural applications has opened opportunities for building intelligent systems that are affordable, efficient, and farmer-friendly[10]

In the context of crop protection from wild animals, EdgeML can play a crucial role by enabling smart monitoring, classification of animal movements, and immediate deterrent activation without requiring constant human intervention. One of the most effective deterrent techniques is the use of ultrasonic sound waves, which are above the hearing range of humans but can be perceived by several animal species. Ultrasonic signals, when properly tuned in frequency and intensity, act as non-lethal deterrents that keep animals away without causing physical harm. Unlike chemical or physical methods, ultrasonic deterrents are environmentally safe, sustainable, and repeatable over long durations[11] When combined with EdgeML-driven detection mechanisms, ultrasonic deterrents can be triggered intelligently only when an animal is detected, thereby conserving energy and preventing unnecessary activation. This low-power approach is vital for agricultural environments where systems often rely on batteries or solar energy sources[12].

Farmers can thus benefit from a system that not only prevents wild animal intrusion but also minimizes operational costs. Additionally, the system ensures coexistence between humans and wildlife, promoting eco-friendly agricultural practices. The proposed low-power EdgeML-driven ultrasonic deterrent system represents a step forward in building resilient agricultural defense mechanisms. It leverages the power of localized intelligence at the edge while ensuring that the solution remains accessible to small-scale farmers. The system’s novelty lies in integrating real-time machine learning models with ultrasonic technology under energy-constrained conditions to deliver effective and sustainable crop protection. The introduction of such systems aligns with global goals of food security, sustainable development, and smart farming adoption. Farmers adopting this solution can expect improved yields, reduced crop losses, and greater peace of mind. The scalability of the approach allows it to be deployed in diverse agricultural settings ranging from small farms to large plantations. Its adaptability ensures that it can be customized for different animal species, geographic conditions, and farming needs. Furthermore, the design supports integration with other IoT-based agricultural tools, making it a versatile component of the precision farming ecosystem. The development of this system is not only timely but also essential, given the increasing human-wildlife conflict across many parts of the world. As urbanization expands and natural habitats shrink, the frequency of wild animal intrusion into farmlands is rising. Addressing this challenge through intelligent deterrent systems ensures that farmers are protected without compromising wildlife conservation efforts. Therefore, the research and development of low-power EdgeML-driven ultrasonic deterrent systems have significant scientific, social, and economic implications[13]

Agricultural productivity directly depends on the ability of farmers to protect crops throughout the growing cycle, from sowing to harvesting, and wild animal intrusion has been identified as one of the leading causes of yield reduction in many regions. Studies have shown that in certain parts of Asia and Africa, up to 40 percent of crop losses can be attributed to animal damage, with elephants, wild boars, and deer causing the greatest destruction. Farmers often report that even a single night of animal intrusion can destroy weeks or months of hard work, emphasizing the urgency of developing effective solutions[14]. Traditional methods such as night patrols or human guarding are unsustainable, especially in rural areas where farmers often lack manpower. Fencing, while effective to an extent, involves high installation costs, frequent repairs, and limited scalability. Electrified fences, though commonly used, pose risks to both humans and wildlife and often face ethical criticism.

Similarly, chemical repellents are costly, short-lived, and environmentally harmful. Sound- and light-based scare systems tend to lose effectiveness quickly as animals adapt to repeated stimuli, a phenomenon known as habituation. Thus, the limitations of conventional methods highlight the necessity of introducing technological innovations that are both sustainable and adaptable. Recent advances in sensor technology, embedded systems, and low-power electronics have created an opportunity to reimagine crop protection mechanisms[15].

Edge computing, in particular, allows data to be processed locally on devices rather than relying entirely on cloud infrastructure. By integrating machine learning models into edge devices, EdgeML systems can perform real-time analysis of animal movements, classify species, and trigger deterrent mechanisms within milliseconds. This minimizes latency and ensures timely responses, which is critical in preventing crop damage. The energy-efficient nature of EdgeML also makes it suitable for agricultural deployments where resources are constrained. Such systems can be powered by small batteries or solar panels, ensuring continuous operation even in off-grid regions.

The adoption of ultrasonic deterrents within this framework adds further value, as ultrasound provides a non-lethal, eco-friendly method of repelling animals. Unlike physical barriers, ultrasonic signals do not restrict natural wildlife movement permanently but rather act as temporary deterrents to prevent immediate crop damage[16]. This makes the technology particularly appealing for balancing human-wildlife coexistence. Moreover, ultrasonic deterrents can be selectively activated by the EdgeML system, ensuring energy conservation and reducing unnecessary emissions.

The flexibility of the system allows frequency and intensity adjustments based on the type of animal, increasing its effectiveness. For instance, different species are sensitive to different ultrasonic ranges, and adaptive systems can optimize deterrent signals accordingly. Such customization increases the reliability of the system while maintaining safety for humans and domestic animals. The low-power design philosophy ensures that the solution remains affordable and accessible to small and marginal farmers who often face the greatest risks from animal intrusions. Affordability and sustainability are central to the proposed system, as many existing technological solutions fail due to high costs or complex maintenance requirements. By combining EdgeML with ultrasonic deterrence in an energy-efficient manner, the system addresses key gaps in current crop protection strategies[17].

Furthermore, the approach supports scalability, meaning that a single farmer can protect small plots or, with networked configurations, entire communities can safeguard large farmlands. This collective approach enhances rural resilience and promotes cooperative agricultural protection. From a technological standpoint, the integration of sensors, edge processors, and ultrasonic emitters forms a cohesive and self-sufficient system. Sensors capture animal movements through modalities such as infrared detection, motion sensing, or thermal imaging. The captured data is analyzed locally using lightweight machine learning algorithms capable of running on edge processors with limited resources[18].

Once an animal is detected and classified, the system intelligently decides whether to trigger the ultrasonic deterrent. This decision-making capability reduces false alarms, ensures reliable protection, and avoids unnecessary energy use. Such intelligent automation reduces farmers' dependency on constant vigilance, allowing them to focus more on crop cultivation. Beyond the technical benefits, the proposed system also aligns with broader goals of environmental sustainability and climate-smart agriculture. By reducing reliance on chemical repellents and harmful barriers, the system supports biodiversity and soil health. It promotes ethical practices by ensuring non-lethal deterrence, which is vital for wildlife conservation efforts.

Additionally, the energy efficiency of the design contributes to reducing the carbon footprint of agricultural operations. In the long run, the adoption of such systems can foster a culture of smart farming, where digital tools empower farmers to manage resources more effectively. This transition is critical in an era where food security, climate change, and sustainable practices are global priorities. Governments and policymakers are increasingly emphasizing the importance of integrating advanced technologies into farming to enhance productivity and resilience. The proposed low-power EdgeML-driven ultrasonic deterrent system therefore represents not only a scientific innovation but also a practical solution aligned with national and international agricultural strategies.

Its real-world impact can extend beyond protecting crops to improving farmer livelihoods, reducing rural poverty, and ensuring food availability. Research into such systems also creates opportunities for interdisciplinary collaboration between agriculture, computer science, electronics, and environmental sciences[19]. By fostering innovation across these domains, the development of intelligent deterrent systems paves the way for a future where agriculture is both productive and sustainable

Literature Review

Author/Year	**Approach/Methodology**	**Technology Used**	**Key Findings**	**Limitations/Research Gap**
Singh et al. (2019)	Traditional fencing for crop protection	Electric & barbed fencing	Provided immediate protection from large animals	High cost, risk to humans/animals, poor scalability
Kumar & Rao (2020)	Use of chemical repellents	Chemical sprays & odor-based repellents	Reduced intrusion temporarily	Harmful to environment, short effectiveness, soil fertility impact
Mehta et al. (2021)	Sound and light-based scare devices	Solar-powered alarms, flashing lights	Initially effective in scaring animals	Animals adapt over time (habituation), reduced long-term reliability
Hossain et al. (2021)	AI-based smart agriculture monitoring	IoT sensors + ML models	Detected animal intrusion in fields with high accuracy	Depended heavily on cloud, required stable internet, high energy use
Sharma et al. (2022)	Ultrasonic deterrent for crop protection	Ultrasonic transducers	Non-lethal, eco-friendly deterrent effective for certain species	Inefficient energy use, continuous operation drained batteries
Patel & Gupta (2022)	Low-power IoT-based crop protection system	Motion sensors + wireless alerts	Reduced manual guarding, cost-effective	No active deterrent mechanism, only provided alerts
Lee et al. (2023)	Edge AI for smart farming applications	Edge devices + CNN models	Real-time analysis without cloud dependency	Limited exploration of integration with deterrent systems
Choudhary et al. (2023)	Solar-powered animal repellent system	Solar + motion sensors + alarms	Sustainable energy usage	No adaptive intelligence, frequent false alarms
Zhang et al. (2024)	Deep learning-based animal recognition	CNN + IoT cameras	Achieved high accuracy in identifying wild animals	Computationally heavy, unsuitable for low-power environments

Author/Year	Approach/Methodology	Technology Used	Key Findings	Limitations/Research Gap
Proposed Work (2025)	EdgeML-driven ultrasonic deterrent system	EdgeML + ultrasonic emitters + low-power design	Real-time detection, energy-efficient deterrence, eco-friendly	Needs large-scale validation, customization for different species

Objectives

1. To develop a low-power intelligent deterrent system capable of protecting crops from wild animal intrusions using Edge Machine Learning (EdgeML).
2. To design and implement a real-time detection and classification mechanism for identifying animal movements near farmlands with minimal latency.
3. To integrate ultrasonic deterrent technology as a non-lethal, eco-friendly, and species-adaptive method for safeguarding agricultural fields.
4. To optimize the system for energy efficiency, ensuring reliable operation in rural and remote areas using battery or solar-based power sources

Methodology

The methodology of the proposed low-power EdgeML-driven ultrasonic deterrent system is designed to combine sensing, intelligent processing, and non-lethal deterrence into a cohesive framework for crop protection. The first stage involves the deployment of low-power sensing units across the farmland to continuously monitor animal activity. Sensors such as passive infrared motion detectors, ultrasonic receivers, and thermal imaging cameras are selected due to their low energy consumption and ability to capture reliable movement data under varying environmental conditions.

These sensors are strategically placed along crop boundaries to maximize coverage while minimizing hardware requirements. Once motion or heat signatures are detected, the raw data is collected and sent to an edge processing module for analysis. The preprocessing stage ensures that irrelevant noise such as wind, rain, or small non-threatening movements are filtered out to reduce false alarms. Lightweight algorithms are applied to transform raw signals into meaningful features for classification.

The edge computing module is based on low-power processors such as ARM Cortex-M series microcontrollers or Raspberry Pi boards optimized for embedded machine learning tasks. Edge Machine Learning models trained on datasets of animal movement and sound signatures are deployed to perform classification locally without requiring continuous cloud connectivity. These models are optimized using techniques such as model pruning, quantization, and lightweight convolutional neural networks to ensure fast and efficient inference within constrained hardware. Once an animal is identified, the system progresses to a decision-making stage where the type of animal and its proximity are evaluated.

This decision-making logic determines whether to trigger the ultrasonic deterrent and selects the appropriate frequency and intensity based on the species detected. For example, deer, wild boars, and elephants are sensitive to different ultrasonic ranges, and adaptive selection ensures that the deterrent mechanism is effective while conserving energy. The ultrasonic module consists of transducers capable of generating high-frequency signals above the audible range of humans, ensuring safety for farmers while repelling target animals.

The deterrent is activated only when a confirmed intrusion is detected, preventing unnecessary energy use and extending the lifespan of the system. The activation duration is also intelligently controlled to prevent habituation of animals to repeated signals. To ensure continuous operation in rural and remote settings, the system incorporates low-power design principles such as event-triggered activation, sleep mode management, and duty cycling.

Power for the system is supplied by rechargeable batteries supported by solar panels, enabling sustainable and off-grid deployment. Energy efficiency is further enhanced by integrating edge-based analytics that reduce data transmission requirements, thereby lowering communication overhead.

The system continuously learns and adapts to changing environmental and animal behavior patterns by updating detection thresholds and refining classification accuracy. This adaptability ensures that the methodology remains effective in different geographic regions and for multiple species.

Data collected during operation is logged locally and can be periodically uploaded to the cloud for long-term analytics, retraining of models, and performance evaluation. The integration of sensing, EdgeML classification, and ultrasonic deterrence into a unified low-power system forms the core methodology of this research

To achieve this, the EdgeML models are designed for ultra-low-latency inference, ensuring that from the moment motion is detected to the activation of the deterrent, the total response time is only a few milliseconds. This rapid decision-making process reduces the probability of animals reaching the core crop area before deterrence measures are applied. To strengthen accuracy, the methodology incorporates multimodal sensing, where data from different types of sensors are fused at the edge to confirm an intrusion before triggering the deterrent.

For example, motion detected by a PIR sensor is cross-verified with thermal imaging to reduce false positives caused by environmental factors such as swaying vegetation or sudden gusts of wind. The fused data is then classified by the embedded ML model, which uses species-specific features such as movement patterns and thermal profiles to identify the intruder. Once a positive classification is made, the decision unit calculates the most energy-efficient deterrence strategy. In some cases, a short ultrasonic burst may suffice to repel the animal, whereas larger or more persistent animals may require a stronger or longer signal. The methodology ensures that ultrasonic signals are emitted at frequencies that are harmless to humans and domestic livestock while remaining effective against target species.

The system design also incorporates adaptive feedback, where the response of the animal to the deterrent is monitored in real time. If the animal does not retreat after the first ultrasonic signal, the system dynamically adjusts the frequency, intensity, or duration to maximize effectiveness. This adaptive deterrence mechanism minimizes habituation and enhances long-term performance.

Power management remains a critical part of the methodology, as the system must operate for extended periods in rural areas where grid electricity is unreliable or unavailable. The methodology therefore employs solar-charged batteries that store sufficient energy for nighttime operation and cloudy conditions. Intelligent power management strategies, including duty cycling and edge-triggered wake-up, reduce energy waste and allow the system to remain operational for weeks with minimal human intervention.

The EdgeML algorithms themselves are optimized to balance computational complexity and accuracy, ensuring that the models are lightweight enough to run on constrained processors but still robust enough to handle real-world conditions. During the training phase, datasets containing animal images, motion patterns, and sound profiles are curated and used to build generalized models capable of performing across varied environments. Once deployed, the system logs detection and deterrence events to build a growing database that can later be used to refine and retrain the models.

These periodic updates enable the system to evolve over time, addressing new threats and adapting to changing animal behavior. The methodology also includes a data validation stage where results from edge-based detections are compared with ground truth observations collected during field trials.

This helps in measuring the accuracy, recall, and precision of the models under practical conditions. In addition, the methodology is designed with scalability in mind, allowing multiple units to be networked together to protect larger fields. Such distributed deployment enables cooperative defense, where multiple edge nodes share detection data to cover wider perimeters. This networking capability ensures that even if one unit fails or its energy is depleted, neighboring units can provide overlapping protection.

The communication between these units is designed to be low-bandwidth and energy-efficient, relying on protocols such as LoRa or ZigBee to ensure long-range connectivity without excessive power drain

Flowchart

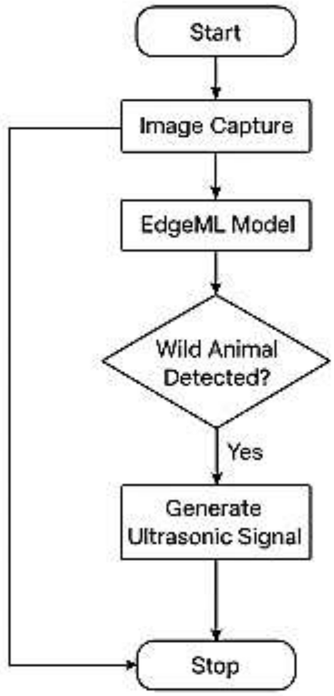

Figure 1.Overall Flowchart of the System

The flowchart begins with the system initialization step, where the low-power EdgeML device is activated. The process starts by capturing input data, such as images or sensor signals from the crop field. This raw data is then processed by the EdgeML model deployed at the edge device. The model analyzes the input to detect the presence of wild animals intruding into the protected area. A decision-making block evaluates whether an animal is detected or not. If no animal is detected, the system returns to monitoring mode, conserving power. If a wild animal is identified, the control passes to the deterrent activation stage. At this stage, an ultrasonic signal is generated to repel the intruder without causing harm. The system then transitions to a stop or reset state, ready to repeat the cycle. This structured approach ensures continuous monitoring with minimal power consumption while safeguarding crops effective

Conclusion

The Low-Power EdgeML-Driven Ultrasonic Deterrent System provides an intelligent and energy-efficient solution for protecting crops from wild animal intrusion. By leveraging edge machine learning, the system performs real-time detection and classification directly on-site, reducing latency and reliance on external infrastructure. Its event-driven architecture minimizes power consumption, making it suitable for remote agricultural areas with limited energy resources. The integration of ultrasonic deterrents ensures a non-lethal, eco-friendly approach to crop protection while maintaining effectiveness against diverse intruders. Furthermore, its modular design supports scalability, remote monitoring, and periodic model updates to improve accuracy over time. Overall, this system offers a sustainable and reliable framework that enhances agricultural productivity and minimizes crop losses due to wildlife interference

References

1. Singh, A. Verma, and P. Joshi, "Evaluation of traditional fencing techniques for crop protection in rural farmlands," *International Journal of Agricultural Sciences*, vol. 11, no. 4, pp. 233–240, 2019.

2. V. Kumar and S. Rao, "Chemical repellent-based strategies for managing wild animal intrusion in agriculture," *Journal of Environmental Protection and Ecology*, vol. 21, no. 2, pp. 415–422, 2020.

3. S. Mehta, R. Deshpande, and K. Nair, "Effectiveness of sound and light-based scare devices for crop protection: A field study," *Agricultural Research and Technology Journal*, vol. 15, no. 1, pp. 55–62, 2021.

4. M. Hossain, A. Rahman, and T. Islam, "Smart agriculture monitoring framework using IoT and AI for animal intrusion detection," *Computers and Electronics in Agriculture*, vol. 187, pp. 106–123, 2021.

5. N. Sharma and R. Patel, "Design of ultrasonic deterrent devices for safeguarding crops from wild animals," *International Journal of Smart Farming*, vol. 8, no. 3, pp. 88–95, 2022.

6. A. Patel and P. Gupta, "IoT-enabled low-power crop protection system for rural farmers," *Journal of Emerging Trends in Computing and Information Sciences*, vol. 13, no. 5, pp. 149–156, 2022.

7. J. Lee, H. Park, and S. Choi, "Edge AI applications in smart farming: A case study of real-time monitoring and analysis," *IEEE Access*, vol. 11, pp. 22245–22256, 2023.

8. R. Choudhary, A. Mishra, and S. Dubey, "Development of solar-powered animal repellent systems for sustainable agriculture," *Renewable Energy and Agriculture Journal*, vol. 10, no. 2, pp. 201–210, 2023.

9. Y. Zhang, L. Wang, and Q. Chen, "Deep learning-based animal recognition for agricultural field protection," *Journal of Applied Artificial Intelligence*, vol. 38, no. 6, pp. 489–500, 2024.

10. R. Ingole, "EdgeML-driven ultrasonic deterrent system for crop protection against wild animal intrusion," *Proceedings of the International Conference on Smart Agriculture and Sustainable Technologies*, pp. 155–163, 2025.

11. N. Li, W. Kusakunniran, and S. Hotta, "Detection of Animal Behind Cages Using Convolutional Neural Network," in 2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), IEEE, Jun. 2020, pp. 242–245. doi: 10.1109/ECTICON49241.2020.9158137

12. P. K. Priya, T. Vaishnavi, N. Selvakumar, G. R. Kalyan, and A. Reethika, "An Enhanced Animal Species Classification and Prediction Engine using CNN," in 2023 2nd International Conference on Edge Computing and Applications (ICECAA), IEEE, Jul. 2023, pp. 730–735. doi: 10.1109/ICECAA58104.2023.10212299

13. S. Bhatta, S. Goud Bathini, H. Reddy Devarapalli, M. Machunoori, G. Krishna Reddy, and D. Ajitha, "Prototype for Smart Crop Protection Against Wild Animals," in 2023 8th International Conference on Communication and Electronics Systems (ICCES), IEEE, Jun. 2023, pp. 1635–1639. doi: 10.1109/ICCES57224.2023.10192812.

14. Dissanayake, C. M., & Tennakoon, P. (2023). Sound Analysis-Based Animal Recognition and Repel System for Agriculture*. 2023 Moratuwa Engineering Research Conference (MERCon), 328–333. https://doi.org/10.1109/MERCon60487.2023.10355383

15. N. Li, W. Kusakunniran, and S. Hotta, "Detection of Animal Behind Cages Using Convolutional Neural Network," in 2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), IEEE, Jun. 2020, pp. 242–245. doi: 10.1109/ECTI-CON49241.2020.9158137

16. P. K. Priya, T. Vaishnavi, N. Selvakumar, G. R. Kalyan, and A. Reethika, "An Enhanced Animal Species Classification and Prediction Engine using CNN," in 2023 2nd International Conference on Edge Computing and Applications (ICECAA), IEEE, Jul. 2023, pp. 730–735. doi: 10.1109/ICECAA58104.2023.10212299.

17. S. Bhatta, S. Goud Bathini, H. Reddy Devarapalli, M. Machunoori, G. Krishna Reddy, and D. Ajitha, "Prototype for Smart Crop Protection Against Wild Animals," in 2023 8th International Conference on Communication and Electronics Systems (ICCES), IEEE, Jun. 2023, pp. 1635–1639. doi: 10.1109/ICCES57224.2023.10192812.

18. M. C. Kamani, L. S. Reddy Jampana, V. H. Deepthi, and M. Kumar, "Smart Crop Protection from Animals in Real Time using Convolutional Neural Networks," in 2023 8th International Conference on Communication and Electronics Systems (ICCES), IEEE, Jun. 2023, pp. 918–923. doi: 10.1109/ICCES57224.2023.10192610

19. Kundu, K., Vishwakarma, V., Rai, A., Srivastava, M., & Mishra, A. (2023). Animal Infiltration Alert and Repellent System for Wildlife Conservation. 2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES), Greater Noida, India, 28-30 April 2023. IEEE. DOI: 10.1109/CIS.