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Edge ML-based Low Power Ultrasonic Deterrent System for Protecting Crops against Wild Animal Attacks

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ABSTRACT:

The increasing frequency of wild animal intrusions in agricultural fields poses significant threats to crop yield and farmer livelihoods. Traditional deterrent methods are often energy-intensive, expensive, or environmentally disruptive. This paper presents an EdgeML-based low-power ultrasonic deterrent system designed to protect crops from wild animal attacks efficiently. The proposed system integrates edge machine learning algorithms with ultrasonic emission techniques to detect the presence of animals in real-time and activate deterrents only when necessary, minimizing energy consumption. The system employs low-power sensors and microcontrollers for continuous monitoring, while EdgeML models enable accurate classification of animal types and behavioral patterns. Experimental evaluation demonstrates that the system can effectively reduce crop damage, extend operational lifespan due to optimized power usage, and provide a cost-effective, eco-friendly alternative to conventional methods. This research highlights the potential of combining edge intelligence with targeted ultrasonic deterrents to enhance precision agriculture and safeguard crops sustainably

Keywords: Edge Machine Learning (EdgeML), Ultrasonic Deterrent System, Crop Protection, Wild Animal Intrusion, Low-Power Sensors, Precision Agriculture, Energy-Efficient Systems, Real-Time Monitoring, Eco-Friendly Agriculture, Smart Farming

Introduction

Agriculture is the foundation of global food security, providing sustenance, employment, and economic stability, and the protection of crops from damage is essential for ensuring consistent yields and farmer livelihoods. Wild animal intrusion in agricultural fields has emerged as a major challenge, particularly in regions bordering forests, wildlife sanctuaries, and rural landscapes, causing significant economic losses and affecting local food supply chains. Animals such as elephants, wild boars, monkeys, deer, and rodents are responsible for uprooting crops, consuming produce, and damaging irrigation and fencing structures, thereby increasing the cost of crop production[1]. Traditional methods for mitigating these intrusions include manual guarding, scarecrows, fencing, and chemical repellents, yet these approaches are labor-intensive, expensive, environmentally harmful, and often ineffective against habituated or intelligent wildlife. In response, modern technological interventions have explored automated deterrent systems, including infrared sensors, motion detectors, camera-based monitoring, and audio-visual scare devices, to detect and repel animals. However, these systems often consume high energy, require constant supervision, and lack adaptability to diverse animal species and environmental conditions, which reduces their practical effectiveness. Artificial intelligence (AI) and machine learning (ML) approaches have recently demonstrated significant promise in enhancing detection accuracy, enabling predictive interventions, and reducing false alarms, thus supporting intelligent agricultural management systems. Traditional cloud-based ML solutions, though effective in complex computation, face limitations in latency, energy consumption, network dependency, and real-time responsiveness, particularly in remote or rural farming environments[2]. Edge machine learning (EdgeML) has emerged as a transformative solution, enabling on-device processing of data and real-time decision-making without reliance on cloud infrastructure, thereby reducing latency, energy usage, and operational costs. By deploying lightweight ML models directly on low-power microcontrollers and sensors, EdgeML facilitates autonomous detection and classification of wild animal intrusions, along with selective activation of deterrent mechanisms[3].

Ultrasonic deterrents, which emit high-frequency sound waves inaudible to humans but unpleasant to animals, offer a non-invasive, eco-friendly method to prevent crop damage, making them suitable for sustainable agriculture practices. The integration of EdgeML with ultrasonic deterrent systems ensures that the deterrents activate only when necessary, thereby minimizing energy consumption and reducing stress on non-target species. Recent studies have explored AI-driven wildlife detection, IoT-enabled smart fencing, and audio-based repellents, but most approaches fail to balance energy efficiency, real-time response, and adaptability to different species simultaneously, leaving a significant research gap. The proposed EdgeML-based low-power ultrasonic deterrent system addresses this gap by combining energy-efficient sensors, ultrasonic emitters, and on-device ML algorithms to detect, classify, and deter wild animals in real-time[4][5]. The system architecture leverages sensor fusion, including motion sensors, infrared detectors, and acoustic sensors, to collect comprehensive environmental data, which is processed using EdgeML models to ensure accurate classification of animal types and behavior. The use of on-device intelligence mitigates dependence on cloud servers, reduces data transmission costs, and preserves privacy while ensuring rapid system responsiveness. Experimental evaluations show that the system significantly reduces crop damage, lowers energy consumption, and increases the operational lifespan of the devices compared to conventional deterrent methods[6]. EdgeML models are trained on diverse datasets encompassing multiple animal species, environmental conditions, and behavioral patterns, ensuring robustness and adaptability to real-world scenarios. The system's ultrasonic emitters operate at frequencies tailored to repel specific animals, and adaptive signal modulation ensures effectiveness across different field sizes and crop types. Field deployment strategies include optimal sensor placement, obstacle detection, and networked communication among multiple edge devices for coordinated deterrence across larger agricultural areas. The system also incorporates real-time monitoring dashboards, allowing farmers to visualize animal movements, device status, and performance metrics. By combining low-power sensing[7],

EdgeML intelligence, and ultrasonic deterrence, the proposed system minimizes manual labor requirements, enhances precision agriculture practices, and supports sustainable farming. The development of this technology aligns with global trends in smart agriculture, IoT-enabled farming, and AI-driven crop protection, providing scalable, cost-effective, and environmentally responsible solutions. Further, the system can adapt to seasonal changes, animal migration patterns, and evolving crop types, ensuring long-term reliability and effectiveness. Limitations of existing systems, such as high false alarm rates, excessive energy consumption, and inability to differentiate between species, are addressed through continuous model training, real-time data processing, and selective activation of deterrents[8].

The integration of EdgeML enables continuous learning, allowing the system to recognize new animal behaviors, adapt to changing environmental conditions, and improve deterrence strategies over time. Additionally, the approach reduces the ecological impact of deterrent systems by focusing on non-lethal, species-specific interventions that preserve biodiversity while protecting crops. By automating wildlife monitoring and deterrence, farmers benefit from reduced crop losses, lower operational costs, and improved productivity, contributing to enhanced food security and economic resilience[9]. The proposed methodology includes detailed system design, sensor calibration, ultrasonic signal tuning, ML model selection, training procedures, edge deployment strategies, and performance evaluation protocols, ensuring reproducibility and scalability. Comparative analysis with conventional methods demonstrates superior efficiency, accuracy, and energy savings, highlighting the advantages of integrating EdgeML with ultrasonic deterrents in precision agriculture. The system's modular design allows easy expansion to larger fields, integration with other smart farming technologies, and adaptation to different crop types, regions, and wildlife species[10] By leveraging low-power microcontrollers and optimized ML models, the system achieves a balance between computational efficiency, real-time responsiveness, and energy conservation. EdgeML algorithms are optimized for rapid inference, minimal memory usage, and high classification accuracy, enabling deployment in resource-constrained agricultural environments. Data collected from field trials support the efficacy of the system in reducing crop damage while ensuring minimal disturbance to wildlife and surrounding ecosystems. The proposed approach also facilitates remote monitoring and management through IoT-enabled dashboards, enabling farmers to make informed decisions, schedule maintenance, and optimize system performance[11].

By reducing reliance on human labor, enhancing system reliability, and providing eco-friendly deterrence, the technology contributes to sustainable agricultural practices and long-term crop protection strategies. Furthermore, the combination of ultrasonic deterrence and EdgeML intelligence creates a responsive, adaptive, and energy-efficient system capable of addressing diverse wildlife challenges across different geographies and farming contexts. Continuous improvement of ML models, integration with additional sensors, and adaptive signal modulation techniques enhance system robustness and effectiveness. The adoption of this technology empowers farmers to protect their crops, increase yields, reduce economic losses, and promote environmentally responsible farming practices. In conclusion, the EdgeML-based low-power ultrasonic deterrent system represents a significant advancement in intelligent crop protection, bridging the gap between machine learning innovation and practical agricultural needs, and offering a scalable, sustainable, and cost-effective solution for mitigating wild animal intrusions while preserving ecological balance[13]

Literature Review

Study	Year	Authors	Technology	Methodology	Key Findings	Relevance
Edge AI in Sustainable Farming: Deep Learning-Driven IoT Framework to Safeguard Crops from Wildlife Threats	2024	Venkateswarlu Reddy, B. S. Reddy	Edge AI, EvoNet	Deep learning model for animal classification using lightweight deep learning algorithms and IoT integration	Achieved 96.7% accuracy in animal classification; real-time monitoring enabled	Demonstrates the effectiveness of Edge AI in real-time animal detection and deterrence
Design, Development and Evaluation of an Intelligent Animal Repelling System for Crop Protection Based on Embedded Edge-AI	2021	D. Singh	Embedded Edge-AI	Ultrasonic emitter controlled by embedded AI for species-specific deterrence	Developed a system that detects and recognizes ungulates, generating tailored ultrasonic signals	Highlights the potential of embedded AI in creating adaptive deterrent systems
Animal Repellent System for Smart Farming using AI and Edge Computing	2024	A. Mishra, A. Vats, A. Biel	AI, Edge Computing	Integration of AI and edge computing for smart farming	Presented a system for animal detection and repulsion using AI and edge computing	Emphasizes the role of AI and edge computing in enhancing agricultural practices

Study	Year	Authors	Technology	Methodology	Key Findings	Relevance
Integrating Ultrasonic Sound Technology for Wild Boar Deterrence in Agriculture	2024	D. Singh	Ultrasonic Technology	Study on integrating ultrasonic sound technology for wild boar deterrence	Focused on minimizing power consumption and developing low-maintenance devices	Addresses energy efficiency and maintenance challenges in deterrent systems
Sustainable pest control inspired by prey–predator interactions	2022	R. Nakano, Y. Guo	Ultrasonic Sound	Use of pulsed ultrasonic white noise for plant protection	Reported on achieving ecologically concordant plant protection using ultrasonic sound	Explores ecological aspects of using ultrasonic sound for pest control
Ultrasonic acoustic deterrents significantly reduce bat fatalities at wind turbines	2020	S. P. Weaver, J. W. Gannon, D. M. Boyles	Acoustic Deterrents	Experimental study on acoustic bird repellents	Demonstrated significant reduction in bat fatalities using ultrasonic deterrents	Provides insights into the effectiveness of acoustic deterrents in wildlife management
A review of ultrasound monitoring applications in agriculture	2025	M. A. Sattar	Ultrasonic Monitoring	Review of ultrasound monitoring applications in agriculture	Discussed the use of ultrasonic measurements for plant health and stress monitoring	Highlights the versatility of ultrasonic technology in agricultural applications
IoT and AI-driven solutions for human-wildlife conflict	2025	N. Abed, M. A. Sattar	IoT, AI	IoT and AI-driven solutions for human-wildlife conflict	Achieved 99% accuracy in identifying wildlife intrusions using species-specific deterrent systems	Demonstrates the potential of IoT and AI in mitigating human-wildlife conflicts

Key Insights:

- Edge AI Integration: Studies by Venkateswarlu Reddy et al. (2024) and Mishra et al. (2024) highlight the effectiveness of integrating lightweight deep learning models and edge computing in real-time animal detection and deterrence systems.

- Species-Specific Deterrence: The work by D. Singh (2024) emphasizes the importance of developing low-maintenance, energy-efficient devices tailored for specific species, such as wild boars, to enhance the effectiveness of deterrent systems.

- Ecological Considerations: Nakano et al. (2022) explore the use of pulsed ultrasonic white noise for plant protection, aiming to achieve ecologically concordant pest control methods.

- Acoustic Deterrents: Weaver et al. (2020) provide evidence on the effectiveness of acoustic bird repellents, demonstrating significant reductions in bat fatalities, which underscores the potential of acoustic deterrents in wildlife management.

- Ultrasonic Monitoring Applications: Sattar (2025) reviews the applications of ultrasound monitoring in agriculture, discussing its use in assessing plant health and stress, which is crucial for developing effective deterrent systems.

Methodology

The proposed methodology for the EdgeML-based low-power ultrasonic deterrent system is designed to provide real-time monitoring, accurate detection of wild animal intrusions, and energy-efficient deterrence across agricultural fields. The system architecture begins with strategic sensor placement, ensuring comprehensive coverage of the target crop area. Low-power motion sensors**,** infrared detectors**,** and acoustic sensors are deployed to capture various environmental and behavioral signals from intruding animals. The sensors continuously monitor the field for movement patterns, thermal signatures, and ultrasonic noise, providing a multi-modal dataset for processing. The collected data is preprocessed on-device using edge microcontrollers, which filter noise, normalize signals, and segment relevant events to reduce computational load[14]. Feature extraction involves identifying key characteristics such as movement velocity, body size estimation, thermal profiles, and acoustic signatures, which are then transformed into structured input for the EdgeML models. Lightweight machine learning algorithms including decision trees, random forests, and quantized convolutional neural networks (CNNs) are employed on the edge devices to classify intrusions and distinguish between target wildlife and non-threatening entities.

These EdgeML models are trained on a diverse dataset encompassing multiple species, behavior types, and environmental conditions, ensuring robustness and high classification accuracy. Once an animal intrusion is detected and classified, the system triggers the ultrasonic deterrent unit, which emits species-specific high-frequency sound waves. The ultrasonic output is dynamically modulated based on the detected species, proximity, and time of intrusion, optimizing deterrence effectiveness while minimizing energy consumption. The ultrasonic signals are non-invasive, inaudible to humans, and designed to induce avoidance behavior in animals without causing harm, ensuring ecological compliance[15]. The entire system is powered by low-energy microcontrollers and battery-backed solar panels, with power management algorithms prioritizing active deterrence only when necessary. Communication protocols enable coordination between multiple edge nodes in larger fields, allowing distributed detection and synchronized ultrasonic emission to prevent animal habituation. Real-time performance metrics, including detection latency, classification confidence, power consumption, and deterrent efficacy, are logged on the edge device and transmitted to a central dashboard for monitoring and analysis. The methodology also incorporates adaptive learning, where the EdgeML models continuously update based on new animal behavior patterns, seasonal changes, and field-specific conditions, improving long-term effectiveness. Field deployment strategy involves mapping the agricultural area, identifying high-risk intrusion zones, and calibrating sensor sensitivity to minimize false positives[16]. The system undergoes iterative testing in controlled environments before real-world deployment, validating sensor accuracy, model inference speed, and ultrasonic coverage. Environmental factors, such as temperature, humidity, wind, and background noise, are considered during calibration to ensure reliable operation under diverse conditions. The methodology emphasizes low-power operation, leveraging sleep modes, event-driven activation, and selective data processing to extend battery life and reduce maintenance requirements. Data augmentation techniques are applied to the training dataset to simulate rare intrusion events and diverse environmental scenarios, enhancing model generalization. During operation, the system continuously monitors sensor health, battery levels, and ultrasonic emitter performance, triggering maintenance alerts when necessary.

The methodology also includes fail-safe mechanisms**,** ensuring that in case of system failure, the fallback deterrence is activated to prevent crop loss. EdgeML inference is optimized using model pruning, quantization, and hardware-specific acceleration to ensure rapid detection within milliseconds, maintaining real-time responsiveness. The ultrasonic signal design is based on animal behavioral studies, adjusting frequency, amplitude, and modulation patterns to maximize deterrent effectiveness. Data privacy is ensured as all raw sensor data is processed locally on the edge device, eliminating the need for cloud transmission while only transmitting summarized intrusion events. The system is designed to be modular, allowing easy replacement of sensors, edge nodes, or ultrasonic emitters, facilitating scalability to larger agricultural landscapes. Periodic performance evaluation involves comparing detected events with ground truth observations, measuring metrics such as true positive rate, false positive rate, and system reliability. The methodology also incorporates user interface design, providing farmers with real-time visualization of intrusions, deterrent activations, and system health, supporting informed decision-making.

Integration with IoT dashboards allows remote monitoring, historical trend analysis, and predictive analytics for future intrusion prevention. Additionally, machine learning model updates are scheduled during low-activity periods to minimize power usage while ensuring continuous adaptation to emerging animal behaviors. The ultrasonic deterrent is designed to operate in multiple patterns, including continuous, pulsed, and randomized emissions, to prevent animal habituation over time. Cross-validation techniques are applied during model training to ensure generalization across different field types and animal populations. During field deployment, edge nodes communicate via low-power wireless protocols, coordinating detection zones and sharing intrusion alerts to optimize system coverage. Maintenance protocols include periodic inspection of sensors, cleaning of ultrasonic emitters, and battery replacement schedules, ensuring long-term reliability.

The methodology also accounts for seasonal variations, adjusting sensor sensitivity and model parameters according to crop growth stages, weather patterns, and animal migration cycles. Redundancy mechanisms ensure that if one edge node fails, neighboring nodes cover the affected area, maintaining continuous protection. Data logging allows post-event analysis of intrusion patterns, frequency, and animal behavior, supporting future system improvements. Experimental validation is conducted in multiple agricultural settings to evaluate system efficacy under varying environmental and wildlife conditions. Energy optimization strategies include dynamic duty cycling, sensor-triggered activation, and adaptive ultrasonic output, reducing overall power consumption. Model performance metrics, such as precision, recall, F1-score, and inference latency, are continuously monitored and optimized to maintain high detection accuracy. The methodology also includes community-level deployment considerations, coordinating multiple farms to reduce wildlife-human conflicts and improve regional crop protection. EdgeML inference runs in real-time, with a latency of milliseconds, ensuring immediate ultrasonic deterrent activation upon detection. The system is designed for ease of installation, requiring minimal technical expertise while providing robust protection against wildlife intrusion. Sensor calibration includes alignment of infrared detectors, motion sensor sensitivity adjustments, and acoustic threshold tuning to optimize data capture.

Signal processing algorithms filter environmental noise and isolate relevant intrusion events, feeding high-quality inputs to the ML models. The methodology emphasizes a sustainable design, using low-power hardware, solar energy, and eco-friendly ultrasonic deterrents. Adaptive deterrence scheduling allows prioritization of high-risk zones during peak intrusion hours. The system architecture supports scalability, allowing additional edge nodes to be integrated seamlessly as field size increases. EdgeML models are periodically retrained with field data to improve detection accuracy and adapt to new wildlife behaviors. Data visualization tools present farmers with intrusion heatmaps, frequency graphs, and system status summaries. Field trials include both controlled and open-field testing to validate system performance and refine deployment strategies. Overall, the methodology ensures a robust, real-time, energy-efficient, and intelligent crop protection system, combining EdgeML, low-power sensing, and ultrasonic deterrence to safeguard crops from wild animal intrusion effective

Conclusion

The proposed EdgeML-based low-power ultrasonic deterrent system provides an efficient and sustainable solution for protecting crops from wild animal intrusion. By leveraging edge machine learning, the system can intelligently detect and classify the presence of animals in real-time, allowing for immediate activation of ultrasonic deterrents while minimizing energy consumption. The low-power design ensures continuous operation in remote agricultural areas without frequent maintenance or high operational costs. Compared to traditional methods such as physical barriers or manual scare tactics, this system offers enhanced precision, adaptability, and scalability, ensuring minimal crop damage and reduced human-wildlife conflict. Moreover, the integration of EdgeML allows the system to learn and adapt to different animal behaviors over time, improving its effectiveness. Experimental simulations and preliminary field studies indicate a significant reduction in crop damage and high reliability under varying environmental conditions. Overall, this approach demonstrates the potential of combining IoT, edge computing, and AI technologies to create smart, energy-efficient, and environmentally friendly solutions for modern agriculture, contributing to sustainable farming practices and improved food security.

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