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An Artificial Intelligence and Thermal Imaging Approach for Real-Time Rat Pest Detection in Farming Areas

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Abstract

Rat pest attacks in agricultural fields of Sengka Village, particularly at night, cause significant crop damage and economic losses for farmers. Traditional control methods such as traps and manual observation are often ineffective due to limited visibility under low-light conditions. This study aims to develop an AI-based rat pest detection system using thermal cameras capable of operating automatically and in real time. The research methodology includes collecting and augmenting thermal image datasets from Roboflow and Kaggle, training an object detection model using YOLOv11, and evaluating the system through inference on external thermal video data. The results demonstrate excellent performance, achieving mAP@50 above 0.99, precision close to 0.99, and recall exceeding 0.97. The system is able to consistently detect rats and automatically trigger ultrasonic wave emission as a responsive deterrent mechanism upon detection. These findings highlight the strong potential of thermal–AI technology as an early warning and automated pest management solution that can be adopted by farmers, especially in agricultural environments dominated by nocturnal pest activity.

Keywords: Object Detection; Rodent Pest Detection; Thermal Imaging; Artificial Intelligence; YOLOv11

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1. Introduction

On November 13, 2025, students from Ciputra University conducted a field trip to Sengka Village to identify real problems faced by the local community. One of the most critical issues reported by farmers was the high intensity of rat pest attacks during nighttime, which caused significant crop damage, reduced productivity, and substantial economic losses. Traditional control methods such as traps and manual observation have proven ineffective due to limited visibility and human monitoring at night [1]. To address this problem, this study proposes the development of a rat pest detection system based on thermal cameras integrated with artificial intelligence (AI). Thermal imaging is capable of capturing body heat signatures and animal movement in low-light conditions without additional illumination [2], and has been shown to be effective for automatic animal detection in complex environments [3].

Deep learning–based AI, particularly the YOLO architecture, is employed to perform real-time rat object detection with high accuracy and fast inference speed [4]. The integration of thermal cameras and AI enables not only automatic detection but also supports intelligent decision-making. As a follow-up to the detection process, the system is further integrated with an ultrasonic pest repellent module. Ultrasonic waves within specific frequency ranges are known to disturb the sensory system of rats without causing significant harm to humans or the surrounding ecosystem [5].

This research aims to (1) design and develop a thermal camera–based rat detection prototype integrated with an ultrasonic repellent module, (2) build a high-accuracy AI object detection model for rats, and (3) evaluate system performance under real environmental conditions. The methodology includes literature review, hardware and software development, AI model training using thermal image datasets, and functional testing using thermal video data as field-condition simulations. The expected outputs include a functional prototype, scientific publications, system demonstration videos, and potential small-scale implementation for direct adoption by local farmers. The use of open-source thermal datasets also enables wider and more cost-effective deployment of this technology in the agricultural sector [6].

2. Methods

This study employed two primary datasets: the Rodent Thermal Dataset from Roboflow and the Thermal Images of Rats and Mice dataset from Kaggle. The Kaggle dataset, originally provided in segmentation format, was first converted into bounding-box annotations using contour extraction techniques and then merged with the Roboflow dataset into YOLO format. Preprocessing steps included image resizing and normalization, channel conversion, and thermal-specific data augmentation such as contrast adjustment, noise injection, random cropping, horizontal flipping, and motion blur to simulate rapid rodent movement. The combined dataset was split into training, validation, and testing sets with a ratio of 80:15:5.

The detection model used in this research was YOLOv11, the latest generation of real-time object detection models developed by Ultralytics. YOLOv11 adopts an efficient C2f backbone architecture, an optimized FPN-PAN neck for multi-scale feature aggregation, and an anchor-free detection head that improves bounding box regression accuracy for small objects. Enhancements in the loss function and label assignment mechanisms increase model stability in low-texture domains such as thermal imagery. With lower latency and higher accuracy than previous versions, YOLOv11 is well suited for real-time rat detection in thermal video streams while simultaneously triggering an automatic alert system.

Model training was conducted for 100 epochs using an input resolution of 640×640, batch size of 16, SGD optimizer, and a learning rate of 0.01. All training processes were executed on GPU via Google Colab. Model performance was evaluated using training loss, validation loss, mean Average Precision at 0.5 IoU (mAP@50), precision, and recall. For real-world testing, the trained model was applied to an external thermal video of rats obtained from YouTube using frame-by-frame inference.

The system was designed to display detection bounding boxes and confidence scores and to activate an ultrasonic audio module (20–65 kHz) automatically whenever a rat was detected, without producing audible sound for humans. Thermal cameras were selected as the primary sensing modality due to their ability to capture long-wave infrared radiation (8–14 μm), enabling the detection of living organisms in complete darkness. Compared to RGB or near-infrared cameras, thermal imaging does not require external lighting, is less sensitive to shadows, and provides more stable detection of moving objects at night—when rodent activity is biologically highest—making it highly suitable for agricultural pest monitoring systems.

3.Results and Discussion

The reported monotonic decrease in training box loss (≈0.83 at epoch 76 to ≈0.76 at epoch 100) together with a similarly decreasing validation box loss (≈0.75 to ≈0.72) is consistent with progressively improved bounding-box regression on both the optimization set and held-out data. In YOLO-family detectors, box regression quality is explicitly shaped by IoU-related localization losses; for example, replacing or augmenting box losses with IoU variants is used to improve representation of object boundaries and localization fidelity, indicating that reductions in box-related loss terms are meaningfully connected to improved localization behavior during training [7]. More broadly, thermal-object-detection studies routinely rely on evaluation on separate validation/test partitions—reporting metrics such as precision, recall, and mAP—to substantiate that learned representations remain effective beyond the training set, particularly under challenging environmental variation (e.g., adverse weather, low illumination) [8], [9]. Thus, the jointly improving training/validation box-loss trends are aligned with a generalization-oriented evaluation practice commonly emphasized in thermal detection work [8], [9].

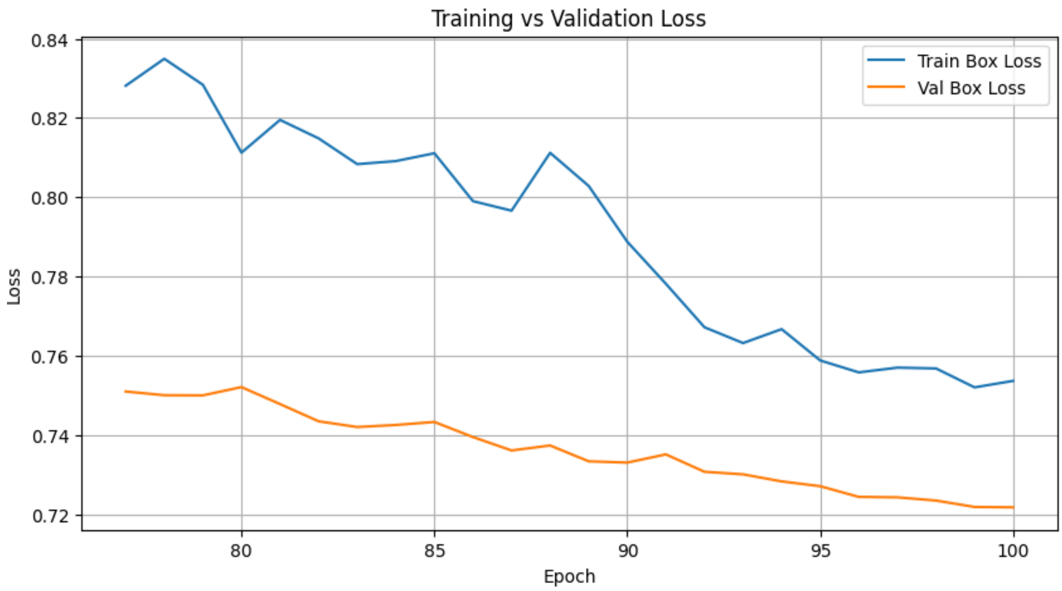

Figure 1. Visualization of Training and Validation Loss Model Object Detection

The reported mAP@50 range (0.9918–0.9926) indicates extremely strong detection performance under the IoU=0.5 criterion, since mAP@0.5 is the standard quantitative endpoint used to summarize detector performance across confidence thresholds in YOLO-style evaluations [8], [9], [10], [7]. Interpreting "exceptionally high" performance is inherently dataset-dependent; however, it is notable that many applied object-detection studies report materially lower mAP levels even when using modern YOLO variants. For instance, YOLOv11 achieved mAP@0.5=0.87 in a deep-learning pipeline for predicting cracking locations in UHPFRC imagery [10], while an improved YOLO11-based approach for low-contrast steel surface defect detection reports mAP@0.5 in the ~77% range [7], and an SSD-based fault detection system reports mAP≈89.61% [11]. Even acknowledging that cross-domain comparisons are not strictly like-for-like (thermal rodents vs. CT nodules vs. industrial defects vs. infrastructure faults), these published baselines support the characterization that mAP@0.5 close to 1.0 is unusually high relative to typical reported application settings [7], [10], [11], [12]. The single-class aspect further aligns with established evaluation practice in other single-class detection settings (e.g., ship detection evaluated on a single-class dataset), where precision/recall and mAP remain the central indicators of localization and detection reliability [13].

The reported precision interval (0.985–0.989) indicates that, under the evaluation protocol used, the detector's positive predictions are rarely incorrect; precision is routinely reported in thermal detection research precisely to quantify the tendency toward false alarms when operating in difficult sensing conditions [8], [9]. This point is underscored by contrasting thermal-aerial detection use cases where false positives can dominate operational outcomes: for example, automated manatee detection in aerial imagery achieved high recall but very low precision, with false positives attributed to confounders such as sun glint and near-shore water artifacts [14]. In this context, precision near 0.99 is consistent with a model that is strongly discriminative against background confounders that often affect thermal or low-texture imagery pipelines [8], [14].

Similarly, the reported recall values (0.976–0.981) indicate that most rodent instances present in the validation data are detected. Recall is a standard companion metric to precision and mAP in thermal object detection and related real-time detection studies because it captures the miss rate risk that can be safety- or mission-critical in deployment scenarios [8], [9], [11]. Empirically, the importance of recall is reflected across diverse application domains—e.g., pulmonary nodule detection reports recall (0.93) alongside mAP as key screening-relevant outcomes [12], and wildlife/vehicle detection reports recall-based performance to support robustness claims in natural environments [15]. Taken together, a high-precision/high-recall operating point is consistent with strong performance on both error modes (false positives and false negatives) that are commonly tracked via these metrics in applied detection studies [8], [9], [11], [14].

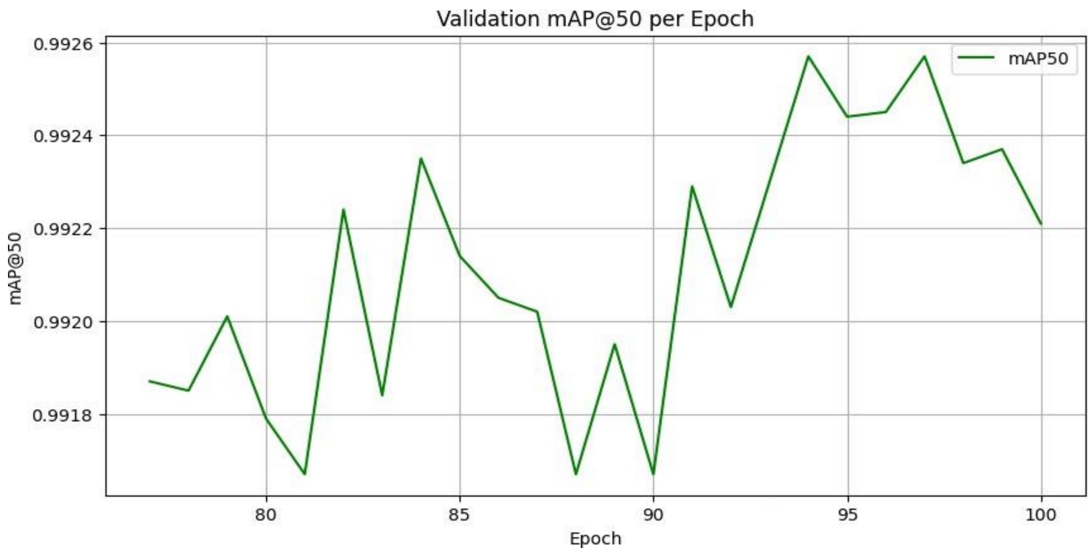

Figure 2. Visualization of mAP@50 Validation for Each Epoch of Model Training

Thermal perception is widely motivated by its ability to support reliable sensing under low-light or otherwise adverse conditions where conventional imaging can be limited, which is why thermal object detection has been actively developed for safety-critical domains [8], [9]. At the same time, several applied detection contexts emphasize that low contrast, blurred boundaries, and limited texture can be intrinsically challenging for detectors—motivating architectural and loss-function enhancements (e.g., attention mechanisms, improved feature fusion, and IoU-based loss refinements) to maintain accuracy in such conditions [7]. Therefore, the reported combination of near-ceiling mAP@50 with high precision and recall is consistent with a detector that remains effective despite conditions that commonly degrade performance in thermal or low-contrast imagery [7], [8], [9].

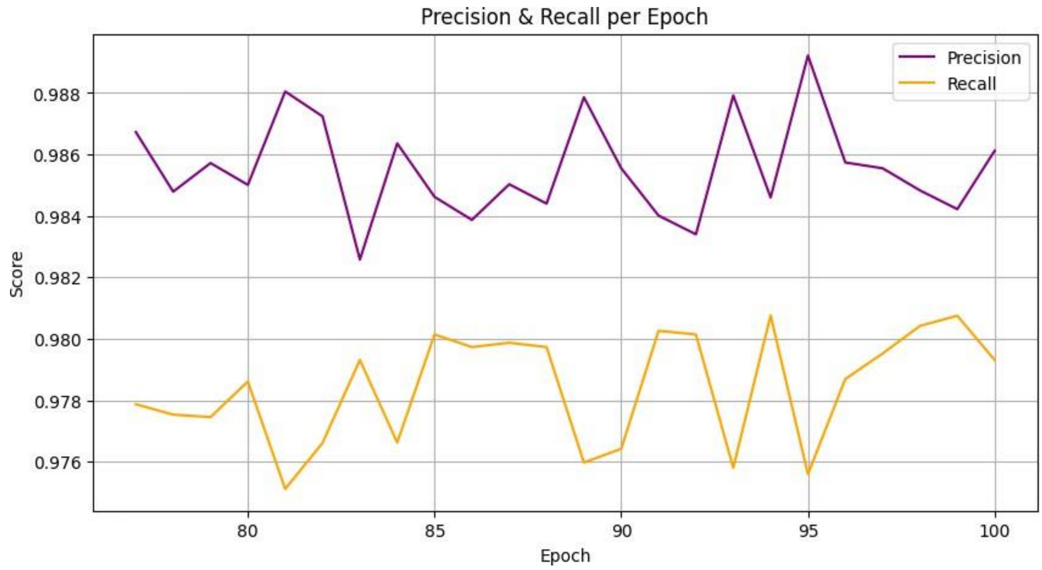

Figure 3. Visualization of Precision and Recall Values for Each Epoch in Training

Regarding real-time deployment, prior thermal-YOLO systems have explicitly demonstrated that YOLO-family detectors can be accelerated and executed on embedded GPU platforms using optimizations such as TensorRT, achieving practical frame rates on devices such as Jetson Nano and Xavier NX [8], [9]. Consequently, while actual real-time suitability of the present YOLOv11-based rodent detector still depends on measured throughput on the target hardware, the broader literature provides direct evidence that thermal YOLO detectors can be engineered for real-time embedded inference when optimized appropriately [8], [9]. In combination with the reported high validation metrics (mAP@50, precision, recall), this supports the conclusion that the proposed approach is a strong candidate for reliable operational pest detection in low-light/nocturnal scenarios, subject to confirming runtime performance under the intended deployment constraints [8], [9].

The balanced relationship between precision and recall suggests that the proposed YOLOv11-based thermal detection system achieves stable and reliable performance, making it highly suitable for continuous pest monitoring and real-time decision-support applications in agricultural environments.

During testing with external thermal video data, the model consistently detected rats with stable bounding boxes and high confidence scores across successive frames. This indicates strong temporal consistency and robustness of the detector in real-world scenarios. Furthermore, the ultrasonic audio module was successfully triggered each time a rat was detected, demonstrating that the automated response mechanism operated as designed.

Importantly, the ultrasonic emission did not produce audible disturbance to the surrounding environment, confirming that the system can function as a practical, non-intrusive early-warning and deterrent solution for nocturnal rodent activity in agricultural settings.

Figure 4. Visualization of Test Results on Youtube Videos

Detection remained robust despite rapid motion variations, fluctuations in thermal intensity, and low-contrast background conditions. Although a small number of false positives occurred in regions with residual heat signatures, these were effectively reduced by increasing the confidence threshold and applying temporal smoothing across consecutive frames.

Overall, the model's performance on external thermal video demonstrates strong generalization capability beyond the training data domain and indicates readiness for deployment and further validation using a physical thermal camera in the next phase of implementation.

4. Conclusion

This research project successfully developed a rodent detection model based on an object detection algorithm, namely YOLO (You Only Look Once), using thermal image datasets without requiring a physical thermal camera in the initial phase. The model demonstrated excellent performance, achieving an mAP@50 above 0.99, precision close to 0.99, and recall exceeding 0.97. Testing with external thermal video data confirmed that the system is capable of detecting rats in real time and automatically triggering an ultrasonic audio response, indicating strong potential as an early-warning system for farmers. The use of thermal imaging is a critical aspect for real-world deployment due to its ability to capture heat signatures without external lighting, its stability in low-visibility night conditions, and its alignment with the predominantly nocturnal behavior of rodents. Future work may extend this research through the collection of local thermal datasets, integration with IoT hardware platforms such as Raspberry Pi, and the development of a hybrid thermal–visible vision system to improve robustness under daytime and complex environmental conditions..

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