



Thermal-based Elephant Detection using YOLOv8 for Automated Wildlife Monitoring in Low-visibility Environments

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ABSTRACT

Background: Human-elephant conflict poses a significant threat to both wildlife conservation and rural livelihoods, particularly in regions bordering forest reserves. Traditional observation methods are often time-consuming, error-prone and limited under challenging environmental conditions, highlighting the need for automated detection systems.

Methods: This study employs the YOLOv8 deep learning framework for elephant detection in thermal imagery. A publicly available thermal elephant dataset from Roboflow was preprocessed to remove low-quality and corrupted images. The dataset included diverse elephant postures, distances and environmental conditions with YOLO-formatted bounding box annotations. YOLOv8 was fine-tuned via transfer learning, utilizing multi-scale detection to localize elephants accurately across varying sizes and thermal scenarios.

Result: The model demonstrated stable convergence, with box, segmentation, classification and distribution focal losses decreasing consistently over 50 training epochs. Detection performance was high, achieving a precision of 0.964, recall of 0.903, mAP@50 of 0.937 and mAP@50-95 of 0.676. Qualitative evaluation confirmed accurate localization under low contrast, motion blur and occlusion. These results indicate that YOLOv8, combined with rigorous dataset preprocessing, provides reliable real-time elephant detection for forest surveillance and early warning systems.

Key words: Deep learning, Elephant detection, Thermal imagery, Wildlife monitoring, YOLOv8.

INTRODUCTION

Human-elephant conflict (HEC) has emerged as a major conservation and livelihood challenge in many parts of Asia and Africa, where expanding human settlements and agricultural land increasingly overlap with traditional elephant corridors (Raza *et al.*, 2025). Elephants often enter farmland in search of food, leading to significant crop damage, property loss and threats to human safety (Montero-Botey *et al.*, 2024). These impacts strain local communities and conservation efforts, requiring effective and timely monitoring strategies to reduce conflict (Prasad *et al.*, 2025).

Conventional methods for elephant monitoring include manual patrolling, ranger observation and camera traps (Fazio *et al.*, 2020). While valuable, these approaches are often labor-intensive, time-consuming and limited by human accessibility. Camera traps and visible-light cameras also struggle with nighttime surveillance or adverse environmental conditions such as fog, rain and dense vegetation (Patel and Sharma, 2022). As a result, many elephant movements remain undetected, limiting the effectiveness of early warning systems (De Mel *et al.*, 2022).

Thermal imaging provides a compelling alternative for wildlife monitoring. Unlike visible-light cameras, thermal sensors capture emitted heat signatures, allowing animals to be detected independent of lighting conditions (Chang *et al.*, 2025). This characteristic makes thermal imagery particularly useful for nocturnal detection and in low-visibility environments. Projects such as the ZSL-based thermal

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dataset initiative demonstrate the potential of thermal cameras for animal detection by identifying heat signatures even when the animal is not clearly visible to standard cameras (Hu *et al.*, 2021; Delwar *et al.*, 2025). Despite these advantages, automated analysis of thermal images remains challenging. Thermal data often suffer from lower resolution, noise, blur from movement and variations in background thermal patterns (Shin and Park, 2025). These issues can degrade the performance of traditional computer vision methods such as HOG/SVM or even some early deep learning models. Therefore, effective preprocessing and robust detection algorithms are essential for reliable elephant detection in thermal imagery (Agaian *et al.*, 2024).

Deep learning has revolutionized object detection, with convolutional neural networks (CNNs) achieving remarkable accuracy in many domains (Kumari and Majumder, 2025). Real-time object detection frameworks

such as YOLO (You Only Look Once) have enabled simultaneous object localization and classification in a single forward pass, making them suitable for real-time applications (Jahan *et al.*, 2025). YOLOv8, the latest iteration of the YOLO family, integrates advanced backbone architectures, optimized neck feature fusion and multi-scale detection heads to improve both accuracy and inference speed (Terven *et al.*, 2023; Swathi and Challa, 2024). This combination makes YOLOv8 a strong candidate for wildlife detection tasks, particularly under challenging imaging conditions.

Recent research has demonstrated the utility of YOLOv8 for wildlife monitoring. For example, state-of-the-art work on automated wildlife detection and tracking using YOLOv8 shows high performance in detecting multiple animal species, including elephants, in complex natural scenes (Roy *et al.*, 2022; Kim, 2025). Other studies have applied YOLOv8 in real-time orchard and farm surveillance to detect animal intrusions, proving its adaptability and real-time capabilities across domains (Sapkota *et al.*, 2024; Sapkota and Karkee, 2024).

However, several research gaps remain. Most studies on wildlife detection focus on visible-spectrum images or camera trap datasets. These methods perform poorly at night or under challenging visual conditions (Mohammad *et al.*, 2026; Paek *et al.*, 2026; Souza *et al.*, 2026). Few studies systematically evaluate YOLO-based models for thermal elephant detection, which is crucial for nocturnal monitoring (Kommalapati *et al.*, 2024; Rizwan *et al.*, 2025). Many automated detection approaches lack rigorous thermal dataset preprocessing. Corrupted images, blur and resolution variation can affect model training and detection (Kim and AlZubi, 2024; Min *et al.*, 2024). Effective filtering and cleaning are needed to ensure high-quality thermal datasets. Finally, while YOLOv8 performs well on general object detection, its real-world performance for thermal elephant detection, including robustness to occlusion, scale variation and temperature background noise, has rarely been studied (Ali and Zhang, 2024).

To address these gaps, this study integrates thermal imaging with the YOLOv8 detection framework to develop a robust elephant detection pipeline. The approach targets key challenges inherent to thermal data and wildlife

monitoring by combining dataset preprocessing, transfer learning and comprehensive evaluation. The work aims to (i) preprocess a publicly available thermal elephant dataset to remove low-quality and corrupted images and maximize the representativeness of the input data (John, 2023), (ii) fine-tune YOLOv8 for elephant detection using transfer learning to use pre-trained feature representations and (iii) assess the model's performance with both quantitative and qualitative metrics, including detection under occlusion, motion blur and low contrast.

MATERIALS AND METHODS

Dataset description (Source and accessibility)

The thermal elephant dataset used in this study was sourced from Roboflow and is publicly available on Kaggle (John, 2023). The dataset consists of pre-annotated thermal images specifically designed for elephant detection tasks. The images were stored in a local directory and served as the input dataset. These images represent real-world thermal surveillance conditions. Such data are commonly affected by blur, noise and variations in resolution. Fig 1 illustrates representative sample images from the training dataset.

Dataset composition

The dataset includes thermal images capturing elephants in diverse postures, orientations, distances and environmental conditions. Both positive samples (images containing elephants) and negative samples (images without elephants) are included, ensuring balanced representation and reducing model bias.

Annotations

Bounding box annotations are provided for elephant instances in each image. The annotations follow the YOLO format, where each text file contains the class ID and normalized bounding box coordinates (center x, center y, width, height), making the dataset directly compatible with YOLO-based detection models.

Data preprocessing and cleaning

To improve detection reliability, a dataset cleaning pipeline was implemented prior to model inference.



Fig 1: Sample images from the training dataset.

Corrupted image removal

Images were checked for corruption or abnormal size. Images with unreadable content or dimensions smaller than 50×50 pixels were removed, as they provide insufficient spatial information for reliable detection.

Image sharpness assessment

Image quality was quantified using the variance of the Laplacian operator, a widely used metric for estimating image sharpness. Images with low sharpness values were considered blurry and unsuitable for detection.

Threshold-based filtering

Minimum resolution thresholds of 100×100 pixels were enforced. Additionally, images falling below the 40th percentile of sharpness scores were discarded. Only high-quality images satisfying both resolution and sharpness criteria were retained in the cleaned dataset.

YOLOv8-based elephant detection

Model architecture and selection

YOLOv8 was selected for elephant detection due to its strong balance between detection accuracy and inference speed. It is a one-stage object detection framework. Object localization and classification are performed in a single forward pass. This design significantly reduces computational overhead and enables near real-time processing. As illustrated in Fig 2, the YOLOv8 architecture consists of three main components: Backbone, Neck and Detection Head. The backbone is responsible for feature extraction. It is composed of convolutional layers and C2f modules that efficiently capture spatial and semantic information. These layers progressively downsample the input image while increasing feature depth. This enables robust representation of thermal patterns. The C2f modules enhance gradient flow and reduce redundancy. They improve learning stability and representation

efficiency. An SPPF (Spatial Pyramid Pooling-Fast) layer is used at the deepest stage of the backbone. This layer aggregates multi-scale contextual information with minimal computational cost. The neck follows a PANet-based feature fusion strategy. It combines top-down and bottom-up pathways. High-level semantic features are fused with low-level spatial features. Upsampling and concatenation operations enable effective multi-scale feature integration. This is critical for thermal imagery, where elephants may appear at varying distances and sizes. The detection head operates at three different scales. Each head predicts bounding boxes, objectness confidence and class probabilities. Small-scale heads detect distant or small elephants. Medium- and large-scale heads focus on closer and larger elephants. This multi-scale prediction mechanism ensures robust detection across diverse thermal scenes.

A pretrained YOLOv8 model was adopted and fine-tuned on thermal elephant images. Transfer learning was applied to initialize model weights. This strategy accelerates convergence and improves generalization. Let θ_0 denote pretrained weights and θ the updated parameters after fine-tuning. The optimization objective is defined as:

$$\theta = \arg \min_{\theta} \mathcal{L}(\theta | \theta_0, D)$$

Where,

D = Thermal elephant dataset.

$\mathcal{L}$ = Total detection loss.

Model deployment and inference

After training, the best model weights were saved as best.pt. These weights were loaded using the Ultralytics YOLO framework. This framework ensures stable deployment and supports efficient inference pipelines. Inference was performed on the cleaned thermal dataset using a confidence threshold of 0.25. A detection is accepted only if the predicted confidence score satisfies:

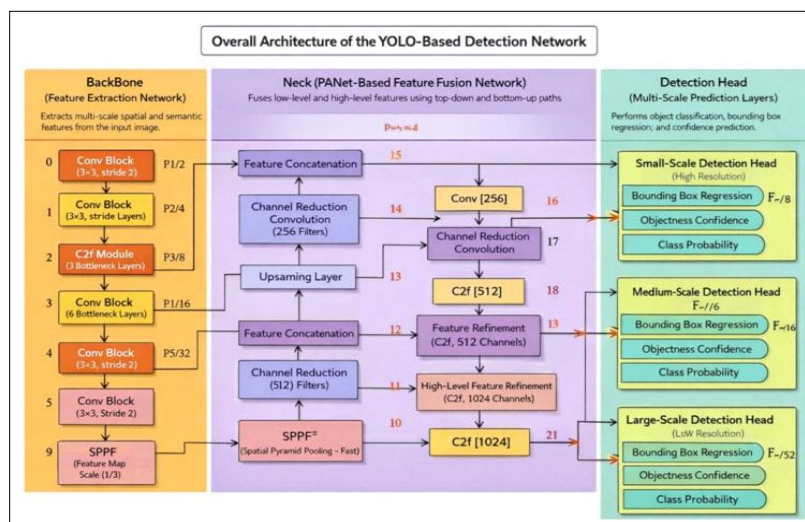


Fig 2: Overall architecture of the YOLO-based detection network.

$$C \geq \tau$$

Where,
 $\tau = 0.25$

This threshold balances detection sensitivity and false positive reduction. Each detection consists of a bounding box and a class probability score. Bounding boxes were overlaid on thermal images along with class labels. All prediction results were automatically saved for visualization and further analysis. The inference resolution was fixed at 640×640 pixels. This resolution provides a compromise between spatial detail and computational efficiency. The inference process can be expressed as:

$$\hat{Y} = f(X; \theta)$$

Where,
 X = Input thermal image.
 f = YOLOv8 network.

$\hat{Y}$ = Predicted bounding boxes and class scores.

Fig 3 shows the overall workflow of the YOLO-based detection network, illustrating each stage from input thermal images to final detection output.

Performance observation

The YOLOv8 model successfully detected elephants across diverse thermal scenes. Both single and multiple elephants were identified accurately. Detection remained robust under variations in background temperature, posture and partial occlusion. Inference time averaged approximately 266 ms per image. Let denote inference time. The average processing speed is given by:

$$T = \frac{1}{N} \sum_{i=1}^N T_i$$

Where,

N = Total number of test images.

This speed supports near real-time applications such as early warning systems. The model maintained stable performance across different elephant scales. Larger elephants yielded higher confidence scores. Smaller or distant elephants were still detected due to effective feature pyramid learning.

RESULTS AND DISCUSSION

Training convergence and loss analysis

Fig 4(a) presents the evolution of the training loss components, including box loss, segmentation loss, classification loss and distribution focal loss (DFL). As shown by the training loss curves, all four loss components exhibit a consistent downward trend, indicating stable convergence and effective learning. The box loss decreased substantially from 2.926 in epoch 1 to 0.764 at epoch 50, reflecting progressive improvement in bounding box localization accuracy. Similarly, the segmentation loss declined from 3.818 to 1.268, demonstrating the model's increasing ability to accurately delineate elephant regions in thermal imagery. The classification loss reduced from 3.273 to 0.740, indicating improved discrimination between elephant objects and background clutter. The DFL loss, which governs bounding box regression quality, steadily decreased from 1.964 to 0.923, confirming enhanced

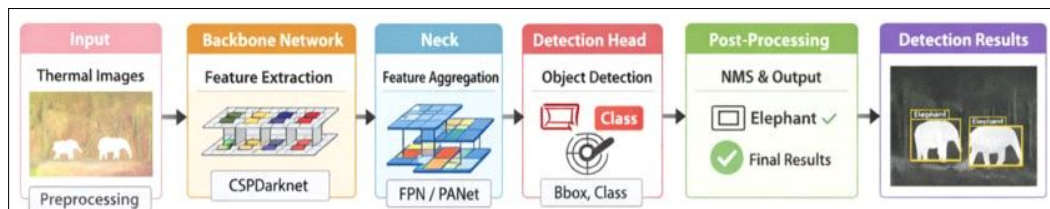


Fig 3: Workflow of the YOLO-based detection network.

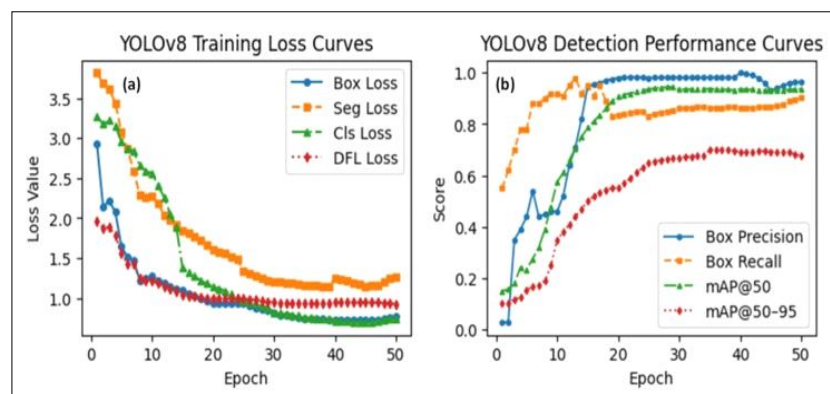


Fig 4: (a) Training loss curves of the YOLOv8 model (b) Detection performance metrics across training epochs.

spatial precision. Minor fluctuations observed after epoch 40 are typical in deep learning training and suggest fine-grained parameter adjustments rather than instability.

Overall, the smooth convergence of all loss components confirms that the model successfully learned robust feature representations from the dataset without signs of overfitting or divergence.

Detection performance evaluation

The detection performance was assessed using precision, recall, mAP@50 and mAP@50-95 across epochs (Fig 4b). Precision improved sharply, rising from 0.028 in the initial epoch to 0.964 by epoch 50, indicating a strong reduction in false positive detections as training progressed. This trend highlights the model's increasing confidence and selectivity when identifying elephants. The recall metric also showed consistent improvement, reaching 0.903 at epoch 50, which demonstrates the model's capability to detect the majority of elephant instances present in the images. The balanced improvement in both precision and recall suggests that the model avoids the common trade-off where gains in one metric significantly degrade the other. The mean Average Precision at IoU 0.5 (mAP@50) reached 0.937, while the stricter mAP@50-95 achieved 0.676 by the final epoch. These values indicate strong detection accuracy under both lenient and stringent localization criteria. The gradual saturation of mAP after approximately epoch 30 suggests that the model reached optimal performance and additional training yielded marginal gains.

Confusion matrix interpretation

The confusion matrix in Fig 5 further illustrates the classification behavior of the model. The model achieved 512 true positives, correctly identifying elephant instances, while only 27 false negatives indicate a low miss rate. Additionally, 21 false positives were observed, representing background regions incorrectly classified as elephants. In object detection tasks, true negatives are not explicitly defined; therefore, the matrix focuses on meaningful detection outcomes.

The combined analysis of loss convergence, detection metrics and confusion matrix demonstrates that the YOLOv8 model is well-suited for elephant detection in thermal

imagery. High precision ensures reliability in automated alerts, while strong recall minimizes the risk of missed detections. The achieved performance indicates significant potential for deployment in human-wildlife conflict mitigation systems, where timely and accurate elephant detection is critical.

Qualitative detection results on thermal images

In addition to quantitative evaluation, qualitative analysis was performed using sample thermal images to visually assess the detection capability of the YOLOv8 model. Representative detection outputs are illustrated in Fig 6, where elephants are correctly localized with high confidence scores of 0.93 and 0.91, respectively.

The results demonstrate that the model is able to accurately identify elephant shapes under challenging thermal conditions, including low contrast, motion blur and background clutter. In the first image (left), the elephant appears partially blurred and frontal in orientation, yet the model successfully encloses the entire body within a tight bounding box. This indicates strong robustness to shape deformation and posture variation. In the second image (right), the elephant is captured in a side-view position with clear limb separation and the detection box accurately aligns with the spatial extent of the animal. The consistently

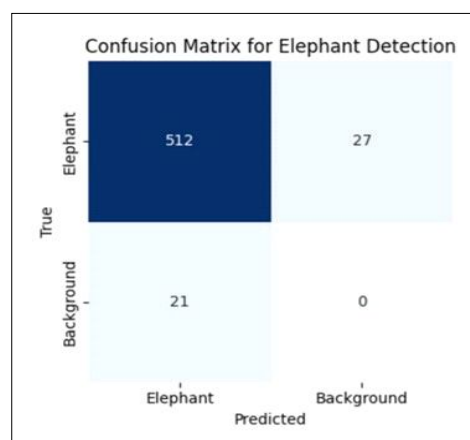


Fig 5: Confusion matrix.



Fig 6: Qualitative elephant detection results.

high confidence scores across different poses and viewing angles confirm that the model has learned discriminative thermal features specific to elephants rather than relying on background cues. Importantly, no spurious detections were observed in the surrounding regions, suggesting effective suppression of false positives. This behavior aligns with the high precision values observed during quantitative evaluation. These qualitative results further validate the effectiveness of dataset cleaning and model training. The use of sharpness-based filtering ensured that low-quality thermal images were removed prior to inference, enabling the model to focus on informative samples. As a result, detection outputs are visually stable and reliable, even when elephants appear blurred or partially occluded. From an application perspective, such reliable visual detection is critical for real-world deployment in forest surveillance and early warning systems.

Several recent studies have explored deep learning-based wildlife detection using YOLO architectures, primarily focusing on multi-species detection and architectural enhancements. Nagaraj *et al.* (2025) proposed a real-time wildlife detection and tracking system based on YOLOv8, trained on approximately 9,000 RGB images to detect multiple animal species, including elephants. Their system demonstrated reliable performance under dense vegetation and low-light conditions, supporting safari management and conservation operations. However, their work relies on visible-spectrum imagery and addresses generalized wildlife detection, whereas the present study specifically targets elephant detection in thermal imagery, which is more suitable for night-time monitoring and low-visibility forest environments. Furthermore, this study provides a detailed analysis of training convergence and thermal-domain performance, which is not explicitly reported in Nagaraj *et al.* (2025).

Chen *et al.* (2024) introduced YOLO-SAG, an improved YOLOv8n-based wildlife detection model that enhances detection accuracy and inference efficiency through architectural modifications, including Softplus activation, AIFI feature interaction and lightweight neck modules. Their contribution lies in optimizing the model structure to reduce computational cost while improving precision, recall and mAP on general wildlife datasets. In contrast, the present work does not modify the YOLOv8 architecture but instead emphasizes domain-specific dataset preprocessing and transfer learning on thermal elephant imagery. Despite using a standard YOLOv8 framework, the proposed approach achieves high detection performance (precision = 0.964, recall = 0.903, mAP@50 = 0.937), demonstrating that careful thermal data preparation and multi-scale training can yield robust real-time performance without increasing architectural complexity.

Roy *et al.* (2022b) proposed WilDect-YOLO, a deep learning-based framework that improves feature extraction through residual blocks, DenseNet modules and enhanced SPP-PANet fusion to support real-time detection of

endangered wildlife in complex environments. While WilDect-YOLO shows strong performance on challenging RGB wildlife datasets, it focuses on multi-species detection and involves increased architectural complexity. By comparison, the present study adopts a lighter and more application-specific approach, concentrating on single-species elephant detection in thermal imagery. The results indicate that multi-scale YOLOv8 detection, combined with rigorous preprocessing, is sufficient to handle occlusion, motion blur and low thermal contrast, achieving reliable localization without additional network modules.

CONCLUSION

This study demonstrates the effectiveness of YOLOv8 for elephant detection in thermal imagery. Through careful dataset preprocessing, including corruption removal, resolution filtering and sharpness assessment-high-quality images were used to train and fine-tune the model. YOLOv8 exhibited strong convergence behavior and robust detection performance across diverse thermal conditions, accurately identifying elephants of varying sizes, poses and orientations. Quantitative metrics (precision, recall, mAP) and qualitative visualizations confirmed the model's reliability for near real-time applications. The approach shows significant potential for deployment in wildlife conservation efforts, including forest surveillance and early warning systems, where timely and accurate detection of elephants is critical. Future work will explore integration with automated alert systems and multi-sensor fusion to enhance detection under extreme environmental conditions.

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Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

Data availability

The author acknowledged Roboflow and Kaggle for providing access to the thermal elephant dataset used in this research. The data analysed/generated in the present study will be made available from corresponding authors upon reasonable request.

Availability of data and materials

Not applicable.

Use of artificial intelligence

Not applicable.

Declarations

Authors declare that all works are original and this manuscript has not been published in any other journal.

Declaration of conflict of Interest

The author declares that he have no conflict of interest.

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