Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 2, April 2026
DOI : https://doi.org/10.33395/sinkron.v10i2.16146
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Field Evaluation of a YOLOv8-Based Drone Video Prototype for Real-Time Tiger Detection and Early Warning

Rangga Rafandi[1], Aisyah Nabilla[2], Dwi Azzahra Siregar[3], Eko Hariyanto[4]*
[1,2,3,4]Universitas Pembangunan Panca Budi, Indonesia
[1]ranggarafandi010703@gmail.com, [2]aisyahnabilla2108@gmail.com, [3]adewi7869@gmail.com,
[4]eko.hariyanto@dosen.pancabudi.ac.id

Submitted :Apr 27, 2026 | **Accepted** : May 3, 2026 | **Published** : May 6, 2026

Abstract: Human–tiger conflict in plantation landscapes remains a critical safety and conservation issue because encounters between workers and tigers can endanger humans while increasing pressure on endangered tiger populations. This study aims to design and conduct a baseline field evaluation of a YOLOv8-based drone video prototype for real-time tiger detection and early warning. The prototype integrates drone-based RGB video acquisition, wireless video transmission, edge-based visual inference, detection logging, and warning output into a single prototype workflow. This study used a systems engineering approach and applied experimentation. The YOLOv8 model was trained using annotated tiger image data and then integrated into the prototype. Field testing was conducted in an open-field baseline scenario using six tiger replicas under two lighting conditions, daytime and evening, to support safety, ethical control, and experimental consistency. System performance was evaluated using precision, recall, F1-score, false negatives, detection range, confidence score, time-to-first-alert, and bounding box stability. The results show that the prototype performed better during daytime testing, achieving 96.90% precision, 85.62% recall, a 90.91% F1-score, a 35 m maximum detection range, 0.60–0.75 average confidence, and a time-to-first-alert of less than 1 s. In evening testing, performance decreased to 93.57% precision, 55.36% recall, 69.57% F1-score, a 7 m maximum range, 0.40–0.55 average confidence, and 1.8–2.5 s response time. These findings indicate that the prototype provides an initial technical basis for drone-based early warning, but further validation is required using real tiger data, complex plantation environments, higher occlusion levels, and improved low-light sensing before operational deployment can be claimed.

Keywords: real-time tiger detection; drone; YOLOv8; early warning; computer vision

INTRODUCTION

The conflict between humans and wildlife has become an increasingly important environmental and socio-economic issue in Indonesia, especially in areas experiencing deforestation and land conversion. In Sumatra, the expansion of agricultural and plantation areas has reduced the natural habitat of wildlife and increased the frequency of encounters between humans and animals outside their natural ecological space (Figel et al., 2023);(Neo et al., 2022). Among the various forms of conflict, the conflict involving Sumatran tigers has a very high level of urgency because it threatens human safety, disrupts plantation activities, and simultaneously increases pressure on the endangered apex predator (Goodrich et al., 2022);(Patana et al., 2023).

This issue becomes even more relevant in the context of oil palm plantations. This environment has dense vegetation, repetitive background patterns, and partial visual barriers that make it difficult for workers to identify tigers early through direct observation. In such conditions, workers may encounter tigers at close range without having enough time to perform a safe avoidance response. Various mitigation efforts that have been undertaken, such as public discussions, education, and community-based conflict management, have indeed contributed to increased awareness and reduced conflict frequency. However, these efforts have not yet provided an operational early warning mechanism that works in real-time for field users (Widiastuti, 2016). Therefore, the need for a

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 2, April 2026
DOI : https://doi.org/10.33395/sinkron.v10i2.16146

e-ISSN : 2541-2019
p-ISSN : 2541-044X

practical system capable of detecting the presence of tigers earlier and delivering warnings directly before physical contact occurs has become increasingly urgent.

The development of computer vision provides a relevant technological foundation to address this need. Computer vision enables machines to interpret visual data from images or videos, recognise specific patterns, and generate automatic responses in real-time (Szeliski, 2022). In wildlife studies, deep learning approaches have been widely used for species recognition and animal identification through camera trap images (Norouzzadeh et al., 2018); (Schneider et al., 2019); (Willi et al., 2019). At the same time, the YOLO model family has evolved into one of the most widely used object detection approaches because this model performs detection in a single-stage flow, allowing for fast and accurate inference in real-time scenarios (Redmon et al., 2016); (Roy et al., 2022). This potential becomes even greater when the system is combined with drone platforms, as drones are capable of recording moving aerial videos, expanding the scope of observation, and reducing direct human exposure in high-risk locations (AlZubi & Alkhanifer, 2024).

Previous research also shows that tiger recognition can leverage distinctive visual features such as stripe patterns. Deep learning approaches have been used to identify individual tigers based on stripe features, while earlier approaches have explored edge pattern similarity and visual patterns for tiger recognition (Hariyanto et al., 2019); (Shi et al., 2020); (Wu et al., 2024). Nevertheless, most previous research still focused on camera trap datasets, post-recording image analysis, or individual identification tasks rather than an integrated early warning system that uses real-time drone video for operational needs. This gap is significant. Field-oriented mitigation systems must not only accurately recognise visual features related to tigers but also process live video, maintain detection stability under challenging visual conditions, and generate alerts with sufficiently low latency to support preventive actions.

Based on these gaps, this research aims to conduct a baseline field evaluation of a YOLOv8-based drone video prototype for real-time tiger detection and early warning. This research focuses on the design of an integrated system that combines video acquisition through drones, real-time visual processing, and warning delivery into a single operational flow. More specifically, this research examines how the prototype can be designed to support the mitigation of human-tiger conflicts, the level of detection accuracy in initial field tests, and how quickly the system generates alerts after the target enters the camera's field of view. Thus, this research contributes at two levels simultaneously, namely at the system engineering level through the development of an operational prototype and at the initial evaluation level through an assessment framework based on detection accuracy, response speed, and usability for preventive mitigation.

Based on this gap, this research aims to conduct a basic field evaluation of a YOLOv8-based drone video prototype for real-time tiger detection and early warning. This research positions the developed system as a baseline prototype. This research positions the developed system as a baseline prototype. This phase is important because initial testing needs to ensure that the main workflow of the system, namely video acquisition via drone, real-time visual processing, object detection with the YOLOv8 model, data logging, and alert activation, can operate in a single integrated work sequence. This research uses tiger replicas as test objects to ensure the safety of the researchers and to allow for controlled experimental scenarios to evaluate the system's response to variations in distance, observation angles, drone trajectories, and lighting conditions.

LITERATURE REVIEW

Computer vision in wildlife monitoring

The development of computer vision has changed the way researchers process visual data from natural environments. Szeliski (2022) has explained that computer vision enables machines to interpret images and videos, recognise patterns, and make visual-based decisions. In the field of ecology, this approach has evolved from simple image classification to systems capable of detection, localisation, counting, and species identification. This change is important because wildlife monitoring typically faces large volumes of data, variations in poses, uneven lighting, and complex backgrounds. Therefore, computer vision has become a logical methodological foundation for the development of automated and more efficient wildlife monitoring systems (Szeliski, 2022).

At the implementation stage, Norouzzadeh et al. (2018) and Willi et al. (2019) have shown that deep learning is capable of identifying wildlife species from camera trap images with high accuracy and much better efficiency compared to manual labelling (Norouzzadeh et al., 2018)(Willi et al., 2019). Schneider et al. (2019) have also demonstrated that this field is moving from a feature engineering approach to deep learning, particularly for animal re-identification (Schneider et al., 2019). If the three studies are read comparatively, two important points become apparent. First, computer vision has proven effective for automating wildlife monitoring. Second, the majority of early studies still work with passive data, namely, images that have been previously recorded and then analysed offline. In other words, the existing literature has been strong in developing recognition accuracy but has not yet fully addressed the needs of operational systems that must process live video and make immediate decisions.

Another limitation of the camera trap literature lies in the static nature of the observation platform. Camera traps are very effective for documenting wildlife presence, estimating occupancy, and studying behaviour; however,

*name of corresponding author

SinkrOn
JURNAL & PENELITIAN TEKNIK INFORMATIKA
Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 2, April 2026
DOI : https://doi.org/10.33395/sinkron.v10i2.16146
e-ISSN : 2541-2019
p-ISSN : 2541-044X

these cameras rely on fixed installation locations. In conflict mitigation scenarios in large and dynamic work areas, this static nature limits the observation range and reduces response flexibility. Therefore, the evidence from the camera trap literature should be understood as the basis for the model's ability to recognise wildlife, not as a final solution for field early warning systems. Research aimed at active and mobile systems is still needed so that visual recognition capabilities can be translated into tangible operational support.

Drone and real-time object detection

Recent literature has shown that the use of drones in wildlife monitoring is becoming increasingly widespread. Axford et al. (2024) have summarized that deep learning on drone imagery has been used for animal detection, localization, recognition, and combinations of the three (Axford et al., 2024). Iglay et al. (2024) have also shown through end-user surveys that drones are increasingly considered useful in wildlife management, although operational aspects and practical concerns are still being considered (Iglay et al., 2024). At a more recent synthesis level, Aliane (2025) has asserted that the integration of drones and AI opens up significant opportunities for wildlife monitoring in remote and hazardous habitats (Aliane, 2025). Comparing the three studies reveals the evolution of drones from mere aerial recording tools to strategic sensing platforms for conservation. However, most discussions still place drones as observation tools, not yet as part of an integrated early warning system, which limits their potential to proactively address threats to wildlife, such as poaching or habitat loss.

Specifically in the context of tigers, AlZubi & Alkhanifer (2024) have discussed the use of machine learning in drone technology for tracking tigers (AlZubi & Alkhanifer, 2024). That contribution is important because it indicates that drones are indeed relevant for tiger observation. However, the research places more emphasis on the potential for monitoring and tracking, rather than on the system design that connects video acquisition, real-time inference, and direct alert output. This distinction is important. Tracking systems aim to determine the location or movement of wildlife, while early warning systems aim to support rapid preventive actions by field users. Thus, the literature on drones for tigers has provided a strong conceptual foundation but has not yet fully addressed the need for preventive mitigation in complex work environments, such as those involving human-wildlife conflict or habitat encroachment, where timely interventions are crucial.

YOLOv8 object detection model

In the realm of real-time object detection, the YOLO family holds a powerful position. Redmon et al. (2016) introduced YOLO as a one-stage detector approach that views object detection as a single regression problem on bounding boxes and class probabilities. The main advantage of this approach lies in its high inference speed because the entire prediction process occurs in a single computational flow. This characteristic makes YOLO more suitable for real-time scenarios compared to approaches that rely on hierarchical region proposals. For early warning systems, this speed is not just a technical advantage but a functional requirement because inference delays would directly reduce the practical value of the system in the field (Redmon et al., 2016).

Subsequent developments show that YOLO-based architectures continue to be refined for increasingly challenging visual contexts. Zhai et al. (2023) have developed YOLO-Drone based on YOLOv8 optimization for detecting small-sized UAV objects (Zhai et al., 2023). Chen et al. (2024) then developed YOLO-SAG based on YOLOv8n for detecting wildlife in complex environments, aiming to balance accuracy and speed (Chen et al., 2024). Both studies convey the same message. Real-time models are not just about speed. They must also be capable of handling small objects, complex backgrounds, variations in target size, and less-than-ideal observation conditions. Thus, the selection of YOLOv8 in this study has a strong theoretical basis because recent literature has shown that the YOLOv8 family is indeed relevant for the need for rapid detection in challenging visual conditions.

Critically, the YOLO literature for wildlife has also shown a shift in focus. Early studies placed more emphasis on whether wildlife objects could be detected. Newer studies are beginning to emphasize how models remain stable when facing dense natural backgrounds, small objects, and computational limitations. This shift is important because field requirements not only demand classification accuracy but also temporal stability and low latency. From these findings, it can be concluded that the three dimensions of performance, namely accuracy, speed, and stability, have become an increasingly relevant evaluation framework for video-based early warning systems. This conclusion is an inference consistent with the direction of the development of YOLO literature and drone-based wildlife detection.

Tiger recognition

At the species-specific level, tiger recognition research has moved from simple methods to more advanced deep learning models. Hariyanto et al. (2019) have tested an edge pattern-based template matching approach for tiger identification. However, the approach still relies on relatively simple visual representations and has not been designed for dynamic field environments (Hariyanto et al., 2019). Li et al. (2020) through ATRW has introduced a large dataset containing over 8,000 video clips of 92 Amur tigers with bounding box, keypoint pose, and identity annotations. The dataset is important because it presents uncontrolled variations in pose and lighting, making it

*name of corresponding author

closer to real-world conditions (Li et al., 2020). (Shi et al., 2020) then demonstrated that deep convolutional neural networks can leverage stripe patterns for tiger individual identification. (Wu et al., 2024) improved on this line with an enhanced InceptionResNetV2 model, while (Ma et al., 2025) designed a two-stage pipeline for segmentation and re-identification. (Wang et al., 2025) even explicitly highlighted that occlusion and illumination still pose major challenges in the re-identification of tigers in the wild. If these developments are compared, then the direction of the literature becomes clear. The tiger's pattern features are indeed very valuable, but the biggest challenge remains the less-than-ideal field visual conditions. Nevertheless, most tiger re-identification studies still focus on individual recognition, rather than real-time detection for early warning. However, the needs for conflict mitigation are different. The mitigation system does not always require the identity of individual tigers at the initial stage. The system requires faster and sufficiently reliable detection of the tiger's presence so that users can react promptly.

Research gap

Literature synthesis shows that previous research has provided a strong foundation on four main aspects, namely human-tiger conflict mitigation strategies, automation of wildlife recognition based on computer vision, the use of drones for wildlife monitoring, and real-time object detection.

Table 1. Summary of Previous Studies

Study	Focus	Data & Platform	Method	Key Findings	Gap
(Patana et al., 2023)	Human-tiger conflict mitigation strategy	Leuser Ecosystem	SWOT, IFAS, EFAS	Mitigation strategies need to consider internal and external factors.	Still at the strategic level, not yet at the real-time operational system level.
(Norouzzadeh et al., 2018)	Automatic wildlife identification	Camera trap image	Deep learning	Deep learning is capable of automatically recognizing animal species with high accuracy.	Working on static/offline images, not yet on real-time drone-based videos
(Schneider et al., 2019)	Computer vision for animal re-identification	Camera trap image	Review of computer vision methods	Computer vision is effective for identifying individual animals.	Not yet focused on the field early warning system
(AlZubi & Alkhanifer, 2024)	Tracking tigers with drones	Drone	Machine learning	Drones are relevant for monitoring and tracking tigers.	Not yet integrating real-time inference and early warning output
(Zhai et al., 2023)	Optimization of YOLOv8 for small UAV object detection	UAV image	YOLOv8	YOLOv8 is effective for fast detection in aerial images.	Not focused on the tiger object and human-wildlife conflict mitigation
(Shi et al., 2020)	Identify individual tigers based on their stripes.	Tiger image	Deep CNN	Effective stripe patterns for identifying individual tigers	Focus on re-identification, not real-time detection for early warning.
(Wu et al., 2024)	Identification of individual Amur tigers	Tiger image	Improved Inception ResNetV2	Deep learning models improve the accuracy of individual identification.	Not yet directed toward a drone-based early warning system

Based on Table 1, this research occupies a different position. This research not only utilizes drones as an observation platform but also employs YOLOv8 as an object detection model. This research integrates drone video acquisition, real-time visual processing, and early warning output into a single system prototype. Thus, this research contributes conceptually and practically to the development of a drone video-based preventive mitigation system for real-time tiger detection and early warning.

e-ISSN : 2541-2019
p-ISSN : 2541-044X

METHOD

This research uses a systems engineering approach and applied experiments to design and evaluate the initial prototype of a real-time drone video-based tiger detection system. The system is positioned as a baseline prototype, which is an initial prototype used to test the feasibility of the system's basic functions before the system is tested in more complex field conditions. The study aims to ensure that the main components of the system can work together in an integrated manner. This research was conducted through several interconnected stages (see Fig. 1). Problem analysis and system design aim to identify issues and formulate technical solutions, prepare datasets from primary and secondary sources, train the YOLOv8 model using annotated datasets, optimize and export the model for deployment purposes, develop a system prototype that connects drones, computing devices, detection models, and warning interfaces, conduct simulations and field tests, and evaluate the system.

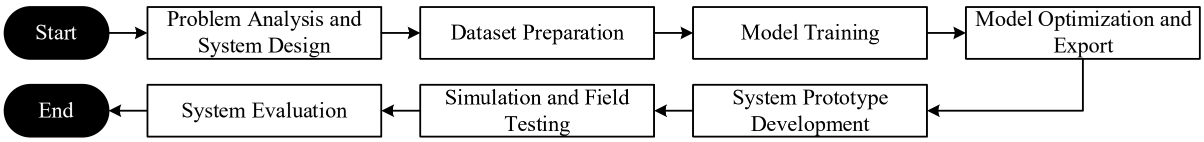

Fig. 1 Research Flowchart

System and Device Architecture

The proposed system architecture can be seen in Fig. 2. The system operates through three main components: a drone as the video acquisition platform, an edge computing device as the visual inference processor, and an output interface as an early warning medium. During the acquisition stage, an RGB camera drone captures video of the observation area in real-time and transmits it via a Wi-Fi network to the edge computing device. In the inference stage, the edge computing device, after receiving the video stream, performs preprocessing such as resizing and normalization, then runs the YOLOv8 model to detect target objects, determine their locations in the form of bounding boxes, and generate confidence values. The system then performs post-processing through confidence filtering and non-maximum suppression to filter out low-confidence predictions and reduce duplicate detections. At the output stage, the system checks for the presence of objects in the tiger class; if an object is detected, the system displays the detection results on the interface in the form of a bounding box, class label, and confidence value, then activates an early warning to the user. Additionally, the system has also recorded all detection events into the data log to support the evaluation of detection stability, tracing of inference behavior, and overall system performance analysis.

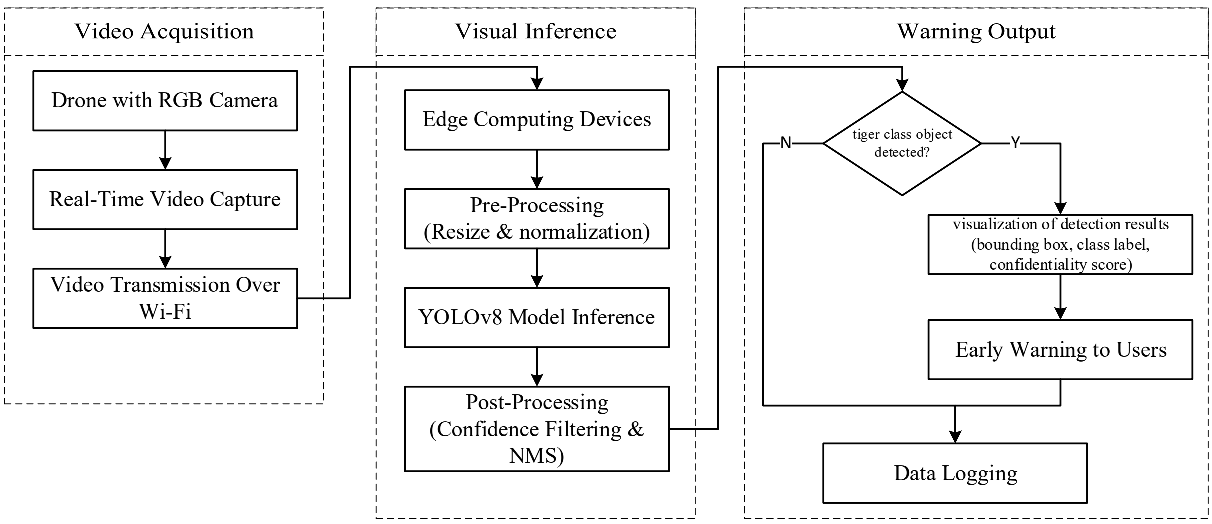

Fig. 2 System Architecture

This research uses two groups of devices, namely acquisition devices and computing devices. The acquisition device used is the DJI Mini 3 RC-N1 drone with a battery capacity of 2453 mAh. The acquisition device is not integrated with additional sensors such as thermal cameras or motion sensors because the test object uses a tiger replica for safety reasons. Meanwhile, the edge computing device used in the system prototype consists of an Intel Core i5 13th Generation processor, an Nvidia RTX 2050 GPU, 16 GB of RAM, and a 512 GB SSD.

*name of corresponding author

SinkrOn
JURNAL & PENELITIAN TEKNIK INFORMATIKA
Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 2, April 2026
DOI : https://doi.org/10.33395/sinkron.v10i2.16146
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Baseline Experimental Design

The initial field tests were conducted in an open environment that had been prepared to support experimental control. The researchers used an open environment so that basic variables such as object distance, object position, drone flight path direction, and lighting conditions could be observed more clearly. The choice of an open environment also aimed to test the basic functions of the prototype before the system was tested in environments with dense vegetation, high occlusion, and complex visual backgrounds. Tiger replicas as target objects were placed in several specific positions. The researchers adjusted the position of the objects to obtain variations in distance and angles relative to the drone's camera. The drone is then flown along a predetermined observation path to record the target object from several angles. This design is used to evaluate the system's ability to detect target objects in drone videos, assess the stability of bounding box visualization, measure detection distance, and calculate the time taken by the system to generate the first alert. This study limits the testing to two lighting conditions, namely bright conditions during the day and dim conditions in the evening. This limitation is made to obtain an initial comparison of the impact of lighting quality on detection performance. This research has not yet tested the system under conditions of rain, fog, dense vegetation, fast-moving objects, heavy occlusion, or the presence of many distracting objects in a single frame.

Research dataset

The research dataset uses two types of data sources, namely primary data and secondary data. Primary data is obtained from image recording using a tiger replica in a testing-prepared environment. The recording captures variations in perspective, distance, and lighting conditions so that the model receives a more diverse set of visual examples. Secondary data has been obtained from the online source, Kaggle. After the data collection is complete, the next step is to annotate all images according to the standard YOLO format. Finally, the dataset is divided into three subsets: training data, validation data, and test data with a ratio of 70:20:10.

YOLOv8 Model

This research uses the YOLOv8 model because it meets the needs of a real-time drone-based system for detecting objects in video. The early warning system requires a model that can process video frames quickly, detect target objects in a single inference flow, and produce detection outputs with a low response time. These requirements align with the characteristics of the YOLO model family, which is designed as a single-stage object detection approach. This approach allows the system to predict the location and class of objects directly without a lengthy region proposal process.The choice of YOLOv8 is also based on its suitability for the system design that uses edge computing devices. The system in this research not only demands detection accuracy but also computational efficiency so that inference can run on field devices. YOLOv8 provides a balance between inference speed and object detection capability, making this model relevant for prototypes that integrate drones, real-time video, computing devices, and early warning outputs. In the context of this research, inference speed plays an important role because detection delays can reduce the functional value of the system as an early warning tool.This study positions YOLOv8 as the baseline model used to test the initial feasibility of system integration. This position is important because the model's performance is still influenced by the quality of the dataset, lighting conditions, object distance, video resolution, camera angle, and the level of visual obstruction in the testing environment. Thus, the evaluation results of YOLOv8 in this study should be understood as a preliminary basis for the development and comparison of models in the next research phase.

Evaluation metrics

This research evaluates system performance through two measurement approaches, namely detection performance and operational performance. For the evaluation of detection performance, this study uses the metrics of precision, recall, and F1-score at a confidence threshold of 0.3, while the evaluation of operational performance is conducted through time-to-first-alert, detection range, number of false negatives, confidence score, and stability of bounding box visualization. This approach was chosen because this research not only evaluates the model's ability to detect objects but also assesses the feasibility of the system as a real-time video-based early warning system. Recall is used to measure the proportion of target objects successfully detected by the system against all target objects that should have been detected (equation 1). Precision is used to measure the proportion of correct detections against all detections produced by the system (equation 2). Meanwhile, the F1-score is used to show the balance between precision and recall (equation 3).

$$Recall = \frac{TP}{TP+FN} \qquad (1)$$

$$Precision = \frac{TP}{TP+FP} \qquad (2)$$

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 2, April 2026
DOI : https://doi.org/10.33395/sinkron.v10i2.16146
e-ISSN : 2541-2019
p-ISSN : 2541-044X

$$F1\text{-}score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (3)$$

Where:

TP (true positive) indicates the number of tiger objects that were correctly detected.

FP (false positive) indicates the number of incorrect detections, where the system detects an object as a tiger when it is not the correct target.

FN (false negative) indicates the number of tiger objects that were not detected.

RESULT

This research successfully implemented a real-time video-based tiger detection prototype that integrates drones as the source of video acquisition and edge devices as the inference processor. Field testing was conducted at two different times: during the day at 1:00 PM and in the evening at 7:00 PM local time, with 50 tests performed at each time. This study used six tiger replicas arranged with a distance of 10 meters between objects. During the testing, the drone flew at an altitude of about 2.5 meters above the ground at a speed of approximately 1 km/h and covered three observation paths: the left side, the right side, and the diagonal.

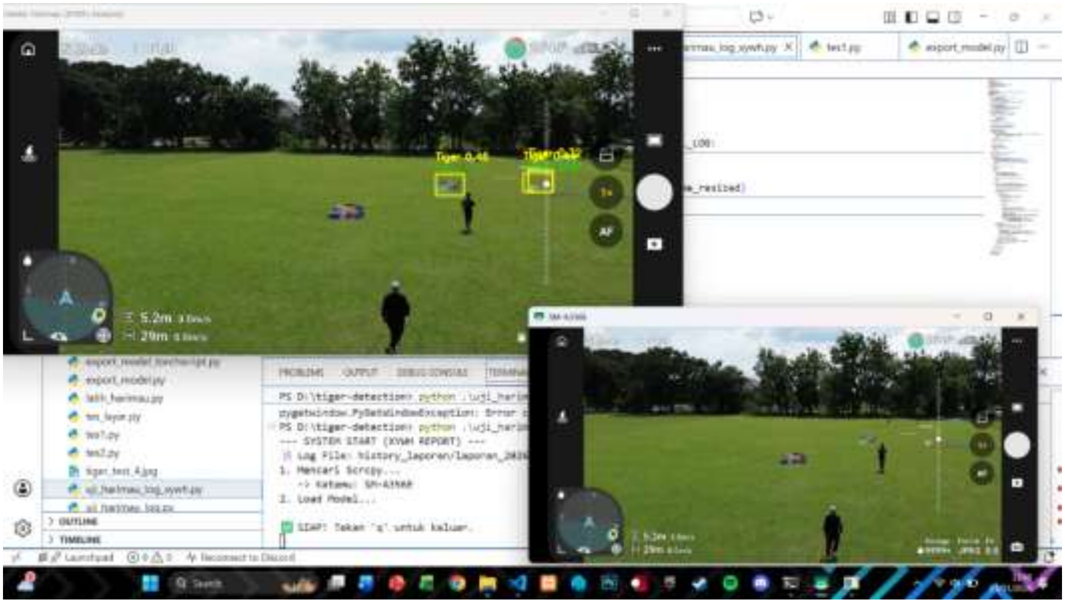

Fig. 3 Field Testing Process During in the Day

Fig. 3 is a screenshot on the edge computing device during the daytime testing process, while Fig. 4 is a screenshot on the edge computing device during the evening testing process. The video displayed on the edge computing device is a video transmitted from the drone in real-time. The test results, both during the day and in the evening, show that the system prototype successfully detected the tiger replica in real-time on the drone video as the targeted object. The system displays a bounding box with the class label "tiger" on the detected object, accompanied by a confidence score for each detection and records all inference processes up to detection into a data log in TXT format. In the edge computing device test display, the system shows bounding boxes, class labels, and confidence values on several objects according to the object placement scenario. These findings indicate that the system can detect multiple objects in a single frame, but it also detects non-tiger objects as tigers (false positives).

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 2, April 2026
DOI : https://doi.org/10.33395/sinkron.v10i2.16146
e-ISSN : 2541-2019
p-ISSN : 2541-044X

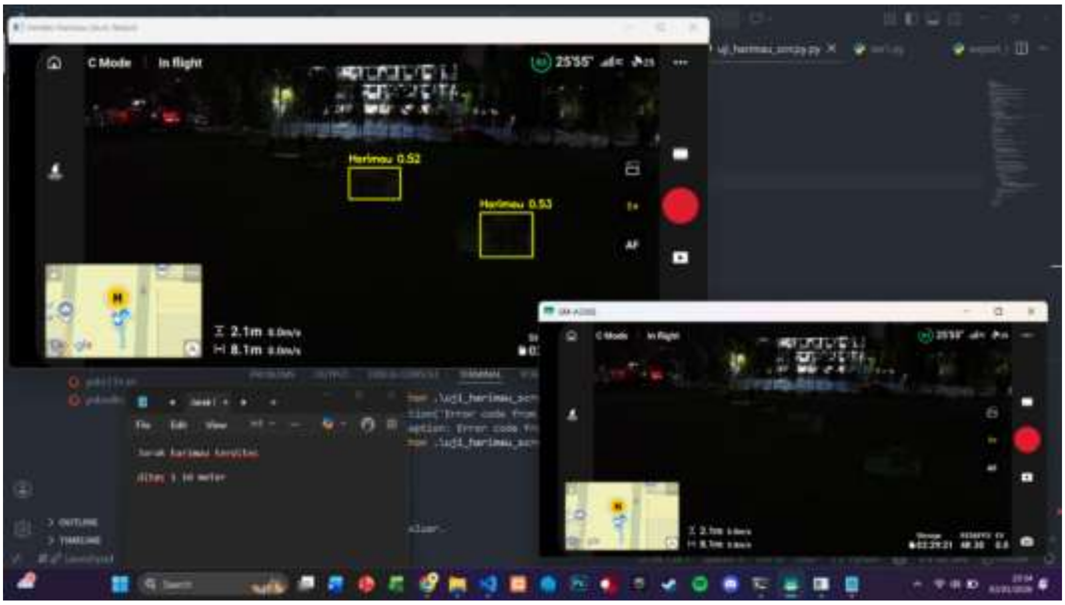

Fig. 4 Field Testing Process During in The Evening

Table 2 is a summary comparison of the prototype system's performance in daytime and evening field tests. This table shows that the system performs better in daytime conditions than in the evening. The system found 250 real objects during the day and 160 real objects at night. The number of false negatives went up from 42 during the day to 129 at night, and the number of false positives went up from 8 to 11. This pattern shows that the decrease in lighting not only reduces the number of objects successfully recognized but also slightly increases the likelihood of false detections.

Table 2. Comparison of prototype performance in day and afternoon testing

Parameter	**The Day (1:00 PM)**	**The Evening (7:00 PM)**
Light condition	Bright (natural)	Dim (spotlight)
Number of correctly detected objects	250	160
Number of missed objects (false negative)	42	129
Number of incorrectly detected objects (false positive)	8	11
Precision	96,90%	93,57%
Recall	85,62%	55,36%
F1-score	90,91%	69,57%
Closest detected object distance	9 meters	5 meters
Farthest detected object distance	35 meters	7 meters
Average confidence score	0,60–0,75	0,40–0,55
Highest confidence	0,77	0,61
Response time (time-to-first-alert)	< 1 seconds	1,8–2,5 seconds
Detection stability (bounding box)	Stable	fluctuating/flickering

From the perspective of evaluation metrics, the system during the day produced a precision of 96.90%, recall of 85.62%, and F1-score of 90.91%. In the afternoon, the system produced a precision of 93.57%, a recall of 55.36%, and an F1-score of 69.57%. These results indicate that the largest decline occurred in recall, not in precision. In other words, in the afternoon, the system is still relatively accurate when providing detections, but it fails to capture many actual target objects. This condition explains why the F1-score also drops significantly, as the balance between precision and recall becomes weaker.

Differences are also observed in the system's response speed. During the day, the system produces a time-to-first-alert of less than 1 second, whereas in the evening, the response time increases to 1.8-2.5 seconds. Additionally, the stability of the bounding box during the day appears stable, whereas in the afternoon it appears fluctuating or flickering. From the perspective of detection range, the system can still detect objects at a minimum distance of 9 meters and a maximum distance of 35 meters during the day. In contrast, in the evening, the system only detects objects within a range of 5 meters to 7 meters. Overall, these results indicate that the system has

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 2, April 2026
DOI : https://doi.org/10.33395/sinkron.v10i2.16146
e-ISSN : 2541-2019
p-ISSN : 2541-044X

functioned more optimally during daytime conditions, both in terms of the number of detections, detection range, confidence value, response speed, and stability of detection result visualization.

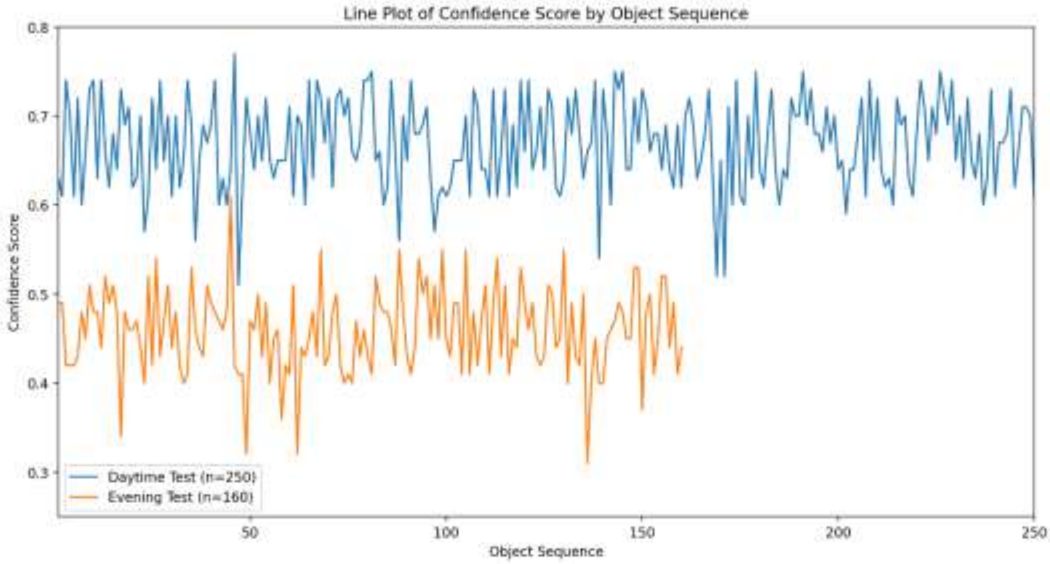

Fig. 5 Line Graph of Confidence Score

Fig. 5 is a line graph showing that the confidence score during daytime testing tends to be at a higher and relatively more stable level compared to evening testing. During daytime testing, the confidence score generally ranges from about 0.60 to 0.75, while during evening testing it ranges from about 0.40 to 0.55, with some drops approaching 0.31.

DISCUSSIONS

The test results indicate that the drone video-based tiger detection prototype using YOLOv8 performs better in daylight conditions compared to evening conditions. In the daytime testing, the system achieved a precision of 96.90%, a recall of 85.62%, and an F1-score of 90.91%. In the evening testing, the system achieved a precision of 93.57%, a recall of 55.36%, and an F1-score of 69.57%. This difference indicates that lighting has a significant impact on the system's ability to maintain detection sensitivity. The system is still able to produce relatively accurate detections when the objects are successfully recognized, but the system loses many target objects under low lighting conditions.

The most significant drop in performance occurs in the recall value. The recall value decreases from 85.62% during the day to 55.36% in the evening. The number of false negatives also increased from 42 objects during the day to 129 objects in the evening. This pattern indicates that the main issue with the system in low-light conditions is not the increase in false detections but the increase in undetected target objects. In the context of an early warning system, this finding is very important because false negatives have more critical operational consequences than false positives. False positives can lead to unnecessary alerts, while false negatives can cause the system to fail to provide an alert when the target object is actually in the observation area.

Technically, the decrease in recall in the afternoon can be explained by the reduced quality of visual information received by the RGB camera. Low lighting conditions can decrease the contrast of the object against the background, reduce the visibility of stripe patterns, increase image noise, and make the object's body boundaries less clear. These conditions can cause the YOLOv8 model to produce a lower confidence score and a less stable bounding box. This is consistent with the test results, which show that the confidence score during the day is in the range of 0.60–0.75, while in the afternoon it drops to 0.40–0.55. The stability of the bounding box also changes from stable during the day to fluctuating in the evening. Thus, the decline in afternoon performance is not only reflected in the classification metrics but is also visible in the system's visual behavior during inference.

The test results also show that lighting conditions affect the detection range and response time of the system. During the day, the system is capable of detecting objects at a distance of up to 35 meters with a time-to-first-alert of less than 1 second. In the evening, the system can only detect objects at a distance of 5–7 meters with a time-to-first-alert of 1.8–2.5 seconds. This difference shows that the decrease in image quality not only reduces the number of detected objects but also narrows the detection range and slows down the activation of alerts. In an early warning system, detection distance and response time are important aspects because both determine how much time users have to take preventive action.

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 2, April 2026 e-ISSN : 2541-2019
DOI : https://doi.org/10.33395/sinkron.v10i2.16146 p-ISSN : 2541-044X

If compared to previous research, the results of this study show a different position. Camera trap-based research has shown that deep learning can recognize wildlife well in previously recorded image data, but most of these approaches still work on static data or post-recording analysis. On the contrary, this research tests the detection workflow on drone video in real-time, so the system challenges are not only related to model accuracy but also to video transmission, inter-frame inference stability, response time, and alert output. Therefore, the main contribution of this research is not only in object detection but also in the initial testing of drone system integration, detection models, edge computing, data logging, and early warning within a single workflow.

The findings of this research are also related to the literature on YOLO and drone-based object detection. The YOLO model is known to be relevant for real-time needs because it performs detection in a single inference stage. This characteristic aligns with the needs of an early warning system that requires a quick response. However, the results of this study indicate that inference speed alone is not sufficient to ensure system reliability in field conditions. Early warning systems require a combination of speed, detection sensitivity, bounding box stability, and resilience to environmental variations. Therefore, this research reinforces the view that the evaluation of drone-based detection systems needs to include operational metrics, not just model accuracy metrics.

At the target object level, the results of this study are also in line with tiger recognition research that emphasizes the importance of visual features such as stripe patterns. These features can indeed help the model recognize objects resembling tigers under good visual conditions. However, the results of the afternoon tests showed that the visual features became less reliable when the lighting decreased. This shows that the RGB camera-based system has fundamental limitations in low-light conditions. Therefore, the next system development needs to consider adding low-light data, image augmentation, adjusting the confidence threshold, improving inter-frame detection stability, or integrating additional sensors such as thermal or infrared cameras.From a methodological perspective, the results of this research should be interpreted as baseline evaluation results of the prototype, not as final evidence of the system's readiness for operational implementation. This research uses tiger replicas as test subjects for safety, ethical, and experimental control reasons. The testing environment is still an open area without complex visual obstacles. Therefore, the results of this study cannot yet be directly generalized for detecting real tigers in plantation environments with dense vegetation, high occlusion, repetitive visual backgrounds, and more extreme lighting variations. This baseline position is important to ensure that the research contribution remains proportional to the experimental design conducted.

The scientific implication of this research is that the evaluation of computer vision-based early warning systems needs to place false negatives as a critical indicator. In general classification systems, high precision is often considered a good result. However, in early warning systems for the safety of humans and wildlife, low recall can reduce the preventive function of the system. Thus, the development of models for the context of human-wildlife conflict mitigation needs to prioritize detection sensitivity, especially under difficult visual conditions. System evaluation also needs to consider the time-to-first-alert because an accurate but slow system can lose its operational value in the field.

Overall, the results of this study indicate that the prototype has successfully performed its basic functions as an early detection and warning system at the baseline stage, especially under good lighting conditions. The system has been able to integrate drone video, YOLOv8 inference, detection visualization, data logging, and alert activation into a single workflow. However, the decrease in recall, narrowing of detection distance, increase in time-to-first-alert, and instability of the bounding box in afternoon conditions indicate that the prototype is not yet reliable enough to be used as a full operational system. Further research needs to test the system on real objects or more representative visual data, environments with dense vegetation, varying levels of occlusion, more controlled low-light conditions, and field scenarios that are closer to the characteristics of plantations.

CONCLUSION

This research shows that the YOLOv8-based drone video prototype is capable of performing basic object detection functions resembling a tiger in real-time and generating early warnings at the baseline evaluation stage. The developed system has integrated video acquisition using drones, YOLOv8-based visual processing, detection result visualization, data logging, and alert activation into a single prototype workflow. Thus, the main contribution of this research lies in the initial testing of system integration, rather than in proving the system's readiness as a fully operational device in a complex plantation environment.

The test results show that lighting conditions significantly affect the system's performance. In daylight conditions, the system produced a precision of 96.90%, a recall of 85.62%, and an F1-score of 90.91%. In evening conditions, the system produced a precision of 93.57%, a recall of 55.36%, and an F1-score of 69.57%. These differences indicate that the system can still maintain a high level of detection accuracy when the object is successfully recognized, but the system's sensitivity significantly decreases in low-light conditions. The decrease in recall and the increase in false negatives indicate that the target object is more often undetected in low-light conditions.These findings have important implications for the development of early warning systems. In the context of human safety and mitigation of human-wildlife conflict, false negatives are a very critical issue because

*name of corresponding author

failing to detect the target object can result in the system missing a warning when a potential danger truly exists. So, the prototype's daytime success can't be used to claim the system is reliable in all field conditions. The system still requires improvements in detection sensitivity, bounding box stability, detection range, and response time, especially in low-light conditions.

This research has several methodological limitations. Testing is still conducted using tiger replicas as test objects for safety, ethical, and experimental control reasons. The testing environment also still consists of open areas without dense vegetation, without high occlusion, and without complex visual backgrounds, as commonly found in plantation areas. In addition, the system still uses RGB cameras without adding additional sensor support, such as thermal or infrared cameras.

ACKNOWLEDGMENT

The author expresses gratitude to the Plantation Fund Management Agency, Ministry of Finance of the Republic of Indonesia, for providing funding support in 2025, enabling this research to be successfully conducted. The author also extends appreciation to the university for providing institutional support, facilities, and assistance throughout the research process.

REFERENCES

Aliane, N. (2025). Drones and AI-Driven Solutions for Wildlife Monitoring. *Drones*, *9*(7). https://doi.org/10.3390/drones9070455

AlZubi, A. A., & Alkhanifer, A. (2024). Application of Machine Learning in Drone Technology for Tracking of Tigers. *Indian Journal of Animal Research*, *58*(9), 1614–1621. https://doi.org/10.18805/IJAR.BF-1759

Axford, D., Sohel, F., Vanderklift, M. A., & Hodgson, A. J. (2024). Collectively advancing deep learning for animal detection in drone imagery: Successes, challenges, and research gaps. *Ecological Informatics*, *83*, 102842. https://doi.org/https://doi.org/10.1016/j.ecoinf.2024.102842

Chen, L., Li, G., Zhang, S., Mao, W., & Zhang, M. (2024). YOLO-SAG: An improved wildlife object detection algorithm based on YOLOv8n. *Ecological Informatics*, *83*, 102791. https://doi.org/https://doi.org/10.1016/j.ecoinf.2024.102791

Figel, J. J., Safriansyah, R., Baabud, S. F., & Herman, Z. (2023). Clustered Conflicts in Disturbed Lowlands Characterize Human–tiger Interactions in Aceh, Indonesia. *Wildlife Letters*, *1*(2), 83–91. https://doi.org/10.1002/wll2.12016

Goodrich, J., Wibisono, H., Miquelle, D., Lynam, A. J., Sanderson, E., Chapman, S., Gray, T. N. E., Chanchani, P., & Harihar, A. (2022). *Panthera Tigris : The IUCN Red List of Threatened Species*. https://doi.org/10.2305/IUCN.UK.2022

Hariyanto, E., Iqbal, M., Siahaan, A. P. U., Saragih, K. S., & Batubara, S. (2019). Comparative Study of Tiger Identification Using Template Matching Approach based on Edge Patterns. *Journal of Physics: Conference Series*, *1196*(1), 012025. https://doi.org/10.1088/1742-6596/1196/1/012025

Iglay, R. B., Jones, L. R., Elmore, J. A., Evans, K. O., Samiappan, S., Pfeiffer, M. B., & Blackwell, B. F. (2024). Wildlife monitoring with drones: A survey of end users. *Wildlife Society Bulletin*, *48*(3), e1533. https://doi.org/https://doi.org/10.1002/wsb.1533

Li, S., Li, J., Tang, H., Qian, R., & Lin, W. (2020). ATRW: A Benchmark for Amur Tiger Re-identification in the Wild. *Proceedings of the 28th ACM International Conference on Multimedia, MM '20*, 2590–2598. https://doi.org/10.1145/3394171.3413569

Ma, Y., Tan, M., Liu, X., Zhang, Y., Xu, Z., Sun, W., Ge, J., & Feng, L. (2025). Deep learning for Amur tiger re-identification in camera traps: A tool assisting population monitoring and spatio-temporal analysis. *Ecological Indicators*, *171*, 113227. https://doi.org/https://doi.org/10.1016/j.ecolind.2025.113227

Neo, W. H. Y., Lubis, M. I., & Lee, J. S. H. (2022). Settlements and Plantations Are Sites of Human–tiger Interactions in Riau, Indonesia. *Oryx*, *57*(4), 476–480. https://doi.org/10.1017/s0030605322000667

Norouzzadeh, M. S., Nguyen, A., Kosmala, M., Swanson, A., Palmer, M. S., Packer, C., & Clune, J. (2018). Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. *Proceedings of the National Academy of Sciences*, *115*(25), E5716–E5725. https://doi.org/10.1073/pnas.1719367115

Patana, P., Alikodra, H. S., Mawengkang, H., & Harahap, R. H. (2023). State of Human Tiger Conflict Around Gunung Leuser National Park in Langkat Landscape, North Sumatra, Indonesia. *Biodiversitas Journal of Biological Diversity*, *24*(2). https://doi.org/10.13057/biodiv/d240220

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 779–788. https://doi.org/10.1109/CVPR.2016.91

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 10, Number 2, April 2026 e-ISSN : 2541-2019
DOI : https://doi.org/10.33395/sinkron.v10i2.16146 p-ISSN : 2541-044X

Roy, A. M., Bhaduri, J., Kumar, T., & Raj, K. (2022). A computer vision-based object localization model for endangered wildlife detection. *Ecological Economics, Forthcoming*. https://doi.org/http://dx.doi.org/10.2139/ssrn.4315295

Schneider, S., Taylor, G. W., Linquist, S., & Kremer, S. C. (2019). Past, present and future approaches using computer vision for animal re-identification from camera trap data. *Methods in Ecology and Evolution*, *10*(4), 461–470. https://doi.org/https://doi.org/10.1111/2041-210X.13133

Shi, C., Liu, D., Cui, Y., Xie, J., Roberts, N. J., & Jiang, G. (2020). Amur tiger stripes: individual identification based on deep convolutional neural network. *Integrative Zoology*, *15*(6), 461–470. https://doi.org/https://doi.org/10.1111/1749-4877.12453

Szeliski, R. (2022). *Computer Vision: Algorithms and Applications* (2nd ed.). Springer.

Wang, T., Ma, B., Zhao, X., Mou, C., & Fan, J. (2025). Pose-Guided Re-Identification of Amur Tigers Under Wild Environmental Constraints. *IET Image Processing*, *19*(1), e70160. https://doi.org/https://doi.org/10.1049/ipr2.70160

Widiastuti, G. (2016). *Model Pengembangan Desa Penyangga Berbasis Kearifan Lokal Sebagai Upaya Penurunan Frekuensi Konflik Manusia Dan Harimau Sumatera Di Taman Nasional Bukit Barisan Selatan (TNBBS)*. Universitas Lampung.

Willi, M., Pitman, R. T., Cardoso, A. W., Locke, C., Swanson, A., Boyer, A., Veldthuis, M., & Fortson, L. (2019). Identifying animal species in camera trap images using deep learning and citizen science. *Methods in Ecology and Evolution*, *10*(1), 80–91. https://doi.org/https://doi.org/10.1111/2041-210X.13099

Wu, L., Jinma, Y., Wang, X., Yang, F., Xu, F., Cui, X., & Sun, Q. (2024). Amur Tiger Individual Identification Based on the Improved InceptionResNetV2. *Animals*, *14*(16). https://doi.org/10.3390/ani14162312

Zhai, X., Huang, Z., Li, T., Liu, H., & Wang, S. (2023). YOLO-Drone: An Optimized YOLOv8 Network for Tiny UAV Object Detection. *Electronics (Switzerland)*, *12*(17). https://doi.org/10.3390/electronics12173664

*name of corresponding author