JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

DEEP LEARNING TECHNIQUE-BASED LOW LIGHT ANIMAL DETECTION AND COLLISION PREVENTION SYSTEM FOR NIGHT-TIME HIGHWAYS

1st G. Satish, 2nd Dr. M. Sailaja
1 Scholar, Department of ECE, JNTUK, Kakinada, India
2 Professor, Department of ECE, JNTUK, Kakinada, India

Abstract : Night-time animal movement on highways can create serious collision risks because reduced illumination makes animals difficult to detect at an early stage. This paper presents a deep learning-based low-light animal detection and collision prevention system for night-time highways. The proposed system uses YOLOv5 for detecting animals in low-light road scenes and extends the detection capability to six classes: Bear, Boar, Deer, Fly, Leopard, and Tiger. The trained detection model achieved a precision of 94.5%, a recall of 95.2%, and a mean Average Precision (mAP) of 96.6% at an Intersection over Union (IoU) threshold of 0.5. To support collision prevention, an application layer is incorporated after detection for the wildlife classes Bear, Boar, Deer, Leopard, and Tiger. Distance estimation is performed using the detected bounding-box dimensions and predefined real-world animal heights. Based on the estimated distance, a driver warning mechanism is used to indicate potentially close animals and support timely driver awareness. The proposed system therefore combines multi-class animal detection with distance estimation and driver warning for a practical night-time highway safety application.

***IndexTerms* - Low-light animal detection, YOLOv5, deep learning, night-time highways, wildlife detection, distance estimation, driver warning, collision prevention.**

I. INTRODUCTION

Night-time driving on highways presents significant safety challenges, particularly in regions where wild animals frequently move across or near roadways. The sudden appearance of an animal on a highway can provide very limited reaction time to the driver and may result in serious animal-vehicle collisions [5]. The risk becomes more significant during night-time because the surrounding illumination is generally low and the visibility of objects on or near the road is reduced. Conventional vehicle headlights may not provide sufficient visibility to identify animals at a safe distance, especially when animals have similar visual characteristics to the surrounding environment. Therefore, an automated system capable of detecting animals under low-light conditions can provide useful information to drivers and support highway safety.

Computer vision and deep learning techniques have become important approaches for automated object detection and recognition. Deep learning based object detection models can identify objects in images or video streams and determine their locations using bounding boxes. Such capabilities make object detection suitable for applications involving road monitoring, intelligent transportation systems, and wildlife protection. However, detection in night-time environments is more challenging than detection under normal illumination because image quality can be affected by insufficient lighting, reduced contrast, shadows, and background interference. These conditions can make it difficult to distinguish animals from the surrounding road and vegetation. Hence, the development of an animal detection system that can operate effectively in low-light environments is an important requirement for night-time highway safety applications.

The You Only Look Once (YOLO) family of object detection models provides a suitable framework for real-time object detection because object localization and classification are performed within a unified detection process. In this work, YOLOv5 is employed for detecting animals in low-light highway scenes. The detection model is trained using a dataset containing six classes: Bear, Boar, Deer, Fly, Leopard, and Tiger. The multi-class detection capability allows the system to identify different animal categories present in the dataset and provides their corresponding bounding-box locations. The detected bounding boxes provide not only information about the type and position of an object but also serve as the input for the subsequent application-level processing.

Although animal detection can identify the presence of an animal, detection alone does not directly indicate how close the animal is to the vehicle. For a collision prevention application, information about the approximate distance of a detected animal is also useful. Therefore, the proposed system incorporates a distance estimation stage after object detection. The distance is estimated using the detected bounding-box dimensions, a focal-length value, and predefined real-world heights corresponding to the relevant wildlife classes. This estimated distance is then used by the driver warning mechanism to provide a proximity-based indication for the detected wildlife. In the distance-estimation and warning stages, the system considers Bear, Boar, Deer, Leopard, and Tiger as relevant wildlife classes. The Fly class remains part of the trained six-class detection model but is ignored during distance estimation and driver warning because it is an insect and is outside the intended wildlife-collision prevention application.

The proposed system therefore extends conventional animal detection by integrating detection, distance estimation, and driver warning into a single application-oriented framework. The objective is not only to identify wildlife in low-light highway environments but also to provide additional proximity information that can assist driver awareness. The system can detect multiple animal classes and subsequently process the relevant wildlife detections for distance estimation and warning generation. This combination provides a practical approach for addressing the limitations of relying only on visual animal detection during night-time highway travel.

The major contributions of this work are the development of a YOLOv5-based six-class animal detection model for low-light scenes, the integration of an application-level distance estimation mechanism for relevant wildlife classes, and the implementation of a driver warning mechanism based on the estimated proximity of detected animals. The trained detection model achieved a precision of 94.5%, a recall of 95.2%, and a mean Average Precision (mAP) of 96.6% at an Intersection over Union (IoU) threshold of 0.5. These results demonstrate the detection capability of the developed model, while the additional distance estimation and warning stages provide a further step toward an application focused on night-time highway collision prevention.

II.RELATED WORK

Deep learning-based computer vision has become an important approach for automated animal detection and wildlife monitoring. Conventional image-processing methods generally depend on manually designed features such as edges, contours, texture, and intensity information. Such approaches can be affected by changes in illumination, background complexity, object scale, and partial occlusion. Deep learning-based object detectors overcome several of these limitations by learning representative features directly from training images and performing object localization and classification within a unified framework.

The YOLO family of object detectors has been widely investigated for real-time object detection because of its ability to provide object localization and classification with comparatively low computational requirements. YOLO-based models have also been applied to wildlife monitoring and animal detection, where rapid identification is important for practical deployment. An automated wildlife monitoring approach based on YOLOv5 with a SENet attention mechanism was developed for animal identification around Kaziranga National Park. The system considered variations in illumination, distance, and background and incorporated an automatic warning mechanism. The reported results demonstrated the potential of YOLOv5-based approaches for real-time animal detection and warning applications. [1]

Another YOLOv5-based wild-animal detection and alert system investigated real-time identification of multiple wild-animal categories from video. The system was designed to generate alerts when animals were detected, demonstrating how object detection can be combined with an alert mechanism for wildlife-related safety applications. [2]

Low-light conditions introduce additional challenges for animal detection because reduced illumination can suppress object details and create uneven brightness, shadows, and glare. To address these issues specifically for night-time highways, Parkavi et al. proposed an enhanced YOLOv5-based animal detection approach using Contrast Limited Adaptive Histogram Equalization (CLAHE) and a Robust Retinex Model for image enhancement. CLAHE was used to improve local contrast, while the Retinex-based processing was used to address illumination variations before the enhanced images were provided to YOLOv5. The authors reported a Precision of 92.3%, Recall of 77.3%, mAP@0.5 of 80.2%, and mAP@0.5:0.95 of 56.7%. These metrics belong to the previously published base study and are therefore considered as related-work results in the present paper. The study also reported that adverse conditions such as rain, fog, and dense foliage can still affect detection performance. [3]

Recent work has continued to investigate deep computer-vision techniques for wildlife monitoring under different illumination conditions. A 2026 study developed a real-time animal monitoring framework using a large dataset covering 46 animal species. CLAHE was applied for image enhancement and YOLOv5 was used for animal localization, with the study reporting an mAP of 80% for the detection stage. The work further investigated deep feature extraction and classification for wildlife identification under daytime, low-light, and nocturnal conditions. [4]

Although existing studies demonstrate the effectiveness of deep learning, image enhancement, and warning mechanisms for animal monitoring, most detection-oriented systems primarily focus on identifying and localizing animals. Detection alone does not directly indicate the approximate distance of an animal from the camera or provide a distance-based indication for driver awareness. Therefore, integrating object detection with distance estimation can provide additional information for a highway safety application. Based on this research gap, the present work extends the animal-detection approach into an integrated software-based collision-prevention framework. The proposed system uses YOLOv5 trained on six classes: Bear, Boar, Deer, Fly, Leopard, and Tiger. The six-class model is used for animal detection, while the Fly class is excluded only from the subsequent distance-estimation and driver-warning stages because it is an insect and is outside the intended animal–vehicle collision scenario. For the remaining animal classes, approximate distance is estimated from the detected bounding-box dimensions using predefined real-world animal heights and camera focal length. The estimated distance is then used by the driver-warning stage to indicate potentially close animals. Thus, the proposed work extends previous animal-detection approaches by combining multi-class detection, approximate distance estimation, and driver warning within a single software-based framework for night-time highway safety.

III.PROPOSED METHODOLOGY

3.1 System Overview

The proposed system is a software-based framework designed for detecting animals in low-light highway environments and providing additional information to support collision prevention. The overall system combines deep learning-based object detection with distance estimation and a driver warning mechanism. YOLOv5 is used as the primary object detection model to identify animals and determine their locations using bounding boxes.

The system begins with a low-light image or highway scene as input. Image enhancement techniques are applied to improve the visibility of relevant image details under reduced illumination. The processed image is then provided to the trained YOLOv5 model for multi-class animal detection. The detection model is trained using six classes: Bear, Boar, Deer, Fly, Leopard, and Tiger. For each detected object, the model provides its class information and bounding-box coordinates.

The detected bounding boxes are subsequently used by the application-level distance estimation stage. Approximate distance is calculated for the relevant wildlife classes using the detected bounding-box height, a predefined camera focal-length value, and predefined real-world animal heights. The Fly class, although included during model training, is not considered in the distance estimation and driver warning stages because it is an insect and is outside the intended animal–vehicle collision prevention application.

Finally, the estimated distance is processed by the driver warning mechanism. When a relevant animal is identified as being potentially close to the vehicle, the system provides a visual warning to increase driver awareness. Thus, the proposed framework integrates low-light image processing, multi-class YOLOv5 detection, approximate distance estimation, and driver warning into a single software-based system for night-time highway safety.

3.2 Dataset Description

The proposed system uses a multi-class wildlife dataset containing six classes: Bear, Boar, Deer, Fly, Leopard, and Tiger. The dataset consists of 1,350 training images, 126 validation images, and 56 test images, with corresponding annotations in YOLOv5 format. The six classes were retained during model training. The Fly class is considered only during detection and is excluded from the subsequent distance-estimation and driver-warning stages, as it is an insect and is outside the intended animal–vehicle collision prevention application.

3.3 Low-Light Image Processing

Night-time highway images often contain insufficient illumination, low contrast, and uneven brightness, which can reduce the visibility of animals and make object detection more difficult. To improve the visual quality of low-light images, the proposed approach considers image enhancement before animal detection. The enhancement stage uses Contrast Limited Adaptive Histogram Equalization (CLAHE) and a Robust Retinex Model to improve the visibility of relevant image regions under low-light conditions.

CLAHE is used to improve local image contrast while limiting excessive contrast enhancement. This helps reveal details in darker regions of the image and improves the distinction between the animal and its surrounding background. The Robust Retinex Model is used to address illumination variations in the input image by separating illumination-related effects from the underlying image information. The combination of these enhancement techniques provides an improved representation of the low-light scene.

The enhanced images are subsequently provided to the YOLOv5-based detection stage. This preprocessing step is intended to improve the visibility of animal features before object detection, thereby supporting the detection of wildlife in night-time highway scenes.

3.4 YOLOv5-Based Animal Detection

YOLOv5 is used as the primary object detection model in the proposed system for identifying wildlife objects in low-light highway scenes. The model performs object classification and localization by generating bounding boxes around the detected objects. This enables the system to determine both the category of an object and its position within the input image.

The enhanced images obtained from the low-light image processing stage are provided as input to the trained YOLOv5 model. The model is trained using the six classes present in the dataset, namely Bear, Boar, Deer, Fly, Leopard, and Tiger. During detection, the model produces the predicted class and corresponding bounding-box coordinates for each detected object.

The bounding-box information obtained from YOLOv5 is further utilized by the subsequent application stages. In particular, the height of the detected bounding box provides the pixel-based measurement required for approximate distance estimation. Therefore, the output of the YOLOv5 detector serves as the link between animal recognition and the subsequent collision-prevention processing.

The trained model provides multi-class detection capability for different wildlife categories within the considered dataset. This allows the proposed system to process multiple animal types using a single detection framework rather than developing separate detection models for individual animal categories.

3.5 Six-Class Detection

The YOLOv5 model is trained on six classes: Bear, Boar, Deer, Fly, Leopard, and Tiger. All six classes are retained during the detection stage. However, for the subsequent collision-prevention processing, only Bear, Boar, Deer, Leopard, and Tiger are considered. The Fly class is ignored during distance estimation and driver warning because it is an insect and is outside the intended animal–vehicle collision scenario.

3.6 Distance Estimation

To provide additional proximity information for detected wildlife, the proposed system estimates the approximate distance between the camera and the detected animal. The estimation uses the height of the detected object in pixels, a predefined real-world height for the corresponding animal class, and the camera focal-length value.

The distance is calculated using the following relation:

$$D = \frac{H \text{ x } F}{P} \qquad (1)$$

where D represents the estimated distance, H represents the real-world height of the detected animal, F represents the camera focal length, and P represents the pixel height of the detected bounding box

In the proposed system, a focal-length value of 800 pixels is used. The real-world height values considered for the relevant wildlife classes are 1.7 m for Bear, 0.9 m for Boar, 1.2 m for Deer, 0.8 m for Leopard, and 1.2 m for Tiger. The pixel height is obtained from the bounding box generated by the YOLOv5 detector.

The calculated distance represents an approximate value and is subsequently used by the driver-warning stage to provide a proximity indication for relevant detected animals. The Fly class is not processed in this stage.

3.7 Driver Warning Mechanism

The driver warning mechanism uses the estimated distance of the detected wildlife to provide a visual indication of potentially close animals. When a relevant wildlife object is detected, its estimated distance is processed by the warning stage, and the detection output is annotated to provide driver awareness.

The warning output displays the detected animal class, estimated distance, and bounding box. For animals identified as requiring a warning, a visual warning indication is generated to draw the driver's attention to the potential hazard. Bear, Boar, Deer, Leopard, and Tiger are considered in this stage, while the Fly class is excluded because it is an insect and is outside the intended animal–vehicle collision prevention application. The resulting output can therefore provide both animal identification and proximity information for supporting driver awareness during night-time highway travel.

IV. RESULTS AND DISCUSSION

4.1 Detection Model Performance

The trained YOLOv5 model was evaluated on the validation data using Precision, Recall, and mean Average Precision (mAP). The model was trained on six classes: Bear, Boar, Deer, Fly, Leopard, and Tiger. It achieved 94.5% Precision, 95.2% Recall, and 96.6% mAP@0.5 at an IoU threshold of 0.5.

The training and validation losses decreased progressively, while precision, recall, and mAP improved and stabilized toward the later epochs, indicating stable model learning and detection performance.

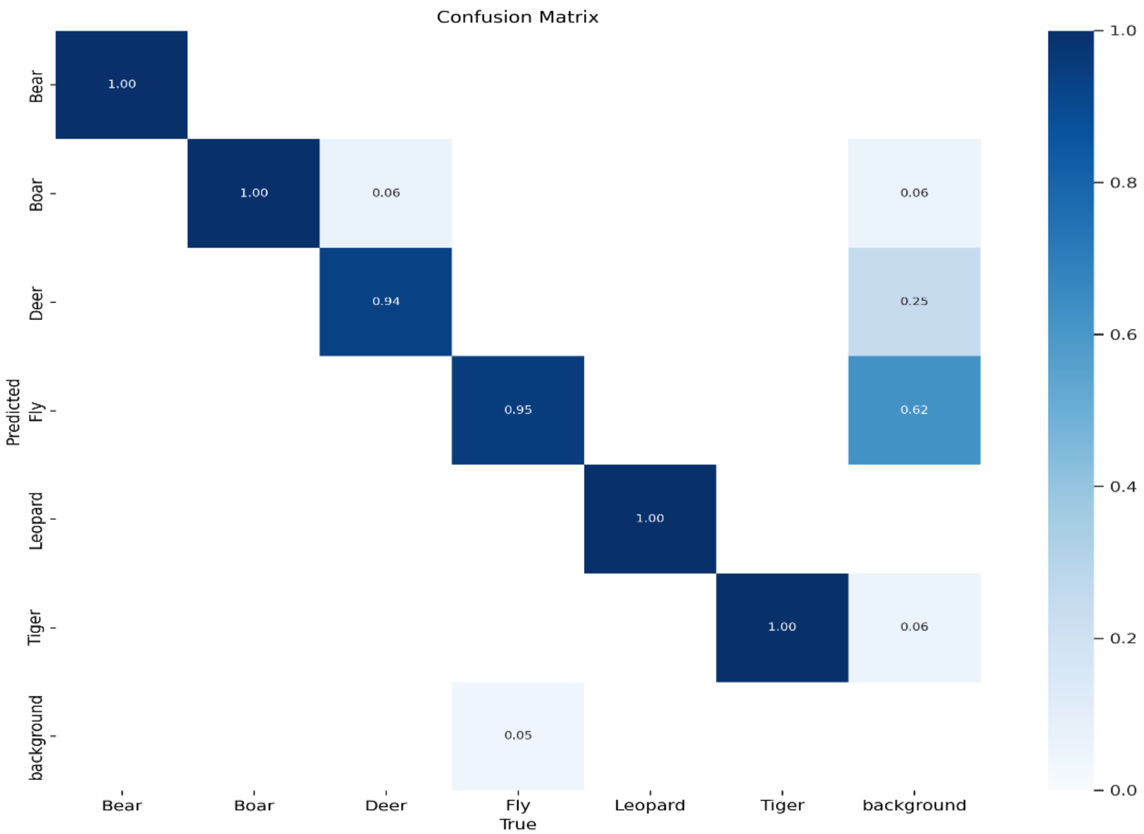

Fig. 1. Confusion matrix of the six-class YOLOv5 detection model

Figure 2 shows the Precision–Recall curve for the six classes. The class-wise curves demonstrate high precision across a large portion of the recall range. The reported average precision values are 0.995 for Bear, 0.957 for Boar, 0.955 for Deer, 0.897 for Fly, 0.995 for Leopard, and 0.995 for Tiger. The overall mAP@0.5 obtained from all six classes is 0.966.

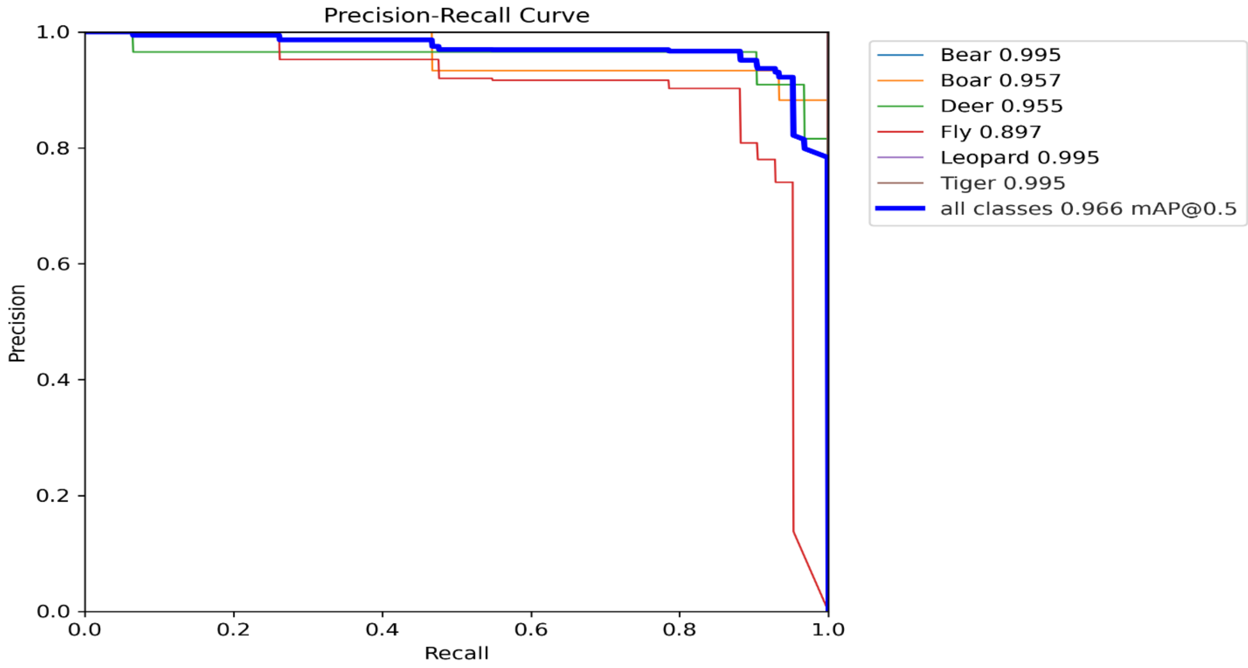

Fig. 2. Precision-recall curve for the six detection classes.

Figure 3 presents the training and validation loss curves together with the precision, recall, mAP@0.5, and mAP@0.5:0.95 metrics. The loss curves decrease during training, while the evaluation metrics improve and become relatively stable toward the later epochs. The mAP@0.5:0.95 curve reaches approximately 0.65 toward the end of training, providing an additional indication of the model's localization performance across different IoU thresholds.

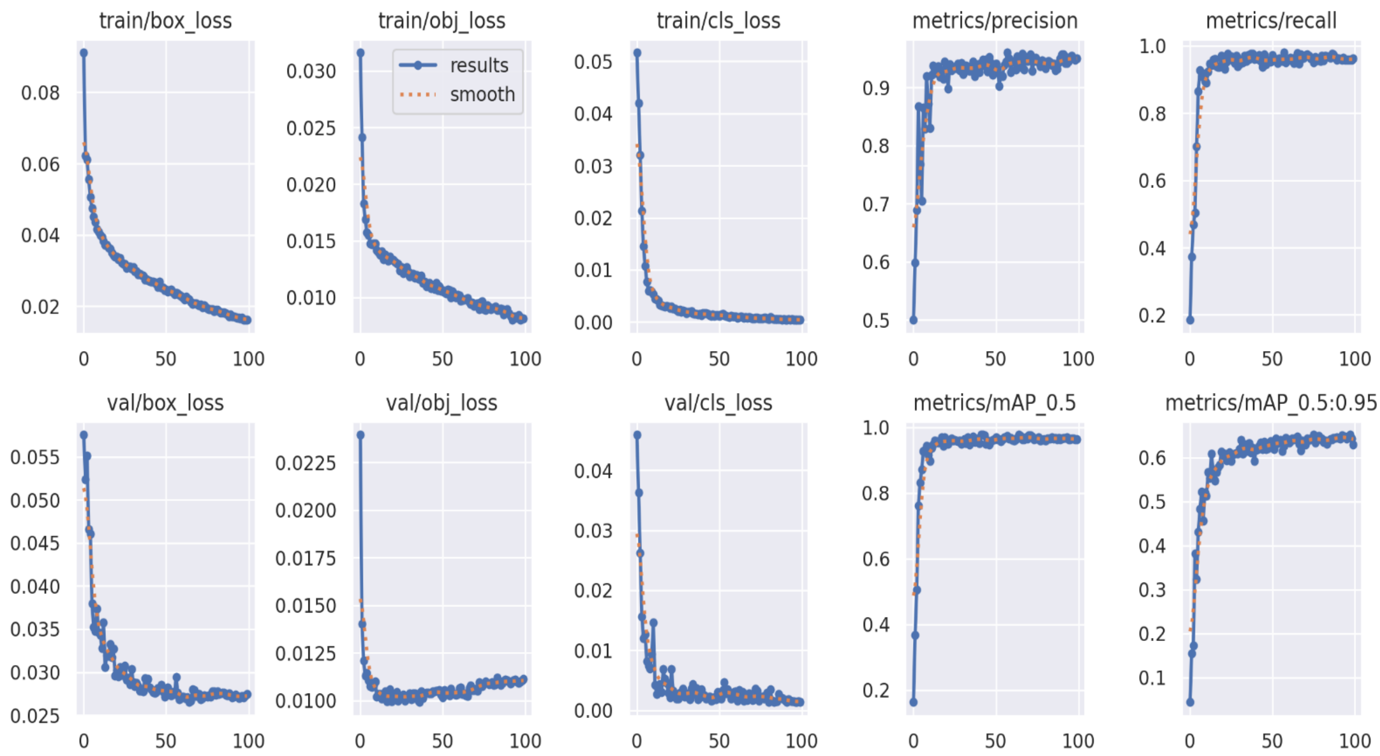

Fig. 3. Training and validation performance of the YOLOv5 model.

4.2 Detection Results

Figure 4 presents representative detection results obtained using the proposed YOLOv5 model under low-light conditions. The model successfully detects different animal classes with bounding boxes and confidence scores. The examples include tiger, deer, and bear detections in nighttime scenes, demonstrating the applicability of the detection model to low-light wildlife images.

Fig. 4. Representative detection results of the proposed YOLOv5 model under low-light conditions.

4.3 Distance Estimation Results

The proposed system estimates the distance of detected animals using the bounding-box pixel height and the corresponding real-world animal height, with a focal length of 800 pixels. Multiple distance estimation outputs were obtained during testing. Figure 5 presents four representative results for tiger, bear, deer, and boar under low-light conditions. The estimated distance is displayed along with the corresponding detected animal label in each output.

Fig. 5. Representative distance estimation results of the proposed system under low-light conditions.

4.4 Driver Warning Results

The driver warning mechanism provides a visual warning when a detected animal is identified as a potential collision risk based on the estimated distance. The detected animal is highlighted with a warning indication to draw the driver's attention toward the potential hazard. Figure 6 presents representative warning and normal detection outputs generated by the proposed system under low-light conditions.

Fig. 6. Representative driver warning and normal detection outputs for detected animals under low-light conditions.

V. CONCLUSION

This work presented a deep learning-based software framework for low-light animal detection and collision prevention during night-time highway travel. The proposed approach combines CLAHE and the Robust Retinex Model for low-light image enhancement with YOLOv5 for detecting six classes: Bear, Boar, Deer, Fly, Leopard, and Tiger. The trained detection model achieved 94.5% precision, 95.2% recall, and 96.6% mAP@0.5, demonstrating effective detection performance under low-light conditions. For the animal classes considered in the collision-prevention stage, distance estimation was performed using bounding-box dimensions and predefined real-world animal heights. A driver warning mechanism was further incorporated to provide visual indications for detected animals that may pose a potential collision risk. Overall, the proposed software-based approach combines low-light enhancement, animal detection, distance estimation, and visual warning to support driver awareness and improve wildlife safety on night-time highways.

REFERENCES

[1] B. Bhagabati, K. K. Sarma, and K. C. Bora, "An automated approach for human-animal conflict minimisation in Assam and protection of wildlife around the Kaziranga National Park using YOLO and SENet Attention Framework," *Ecological Informatics*, vol. 79, Art. no. 102398, 2024, doi: 10.1016/j.ecoinf.2023.102398.
[2] H. A. Jartarghar, M. N. Kruthi, B. Karuntharaka, A. Nasreen, T. Shankar, R. Kumar, and K. Sreelakshmi, "Detection, identification and alert of wild animals in surveillance videos using deep learning," *International Journal of Intelligent Unmanned Systems*, vol. 12, no. 4, pp. 418–432, 2024, doi: 10.1108/IJIUS-09-2022-0125.
[3] K. Parkavi, A. Ganguly, S. Sharma, A. Banerjee, and K. Kejriwal, "Enhancing Road Safety: Detection of Animals on Highways During Night," *IEEE Access*, vol. 13, pp. 36877–36896, 2025, doi: 10.1109/ACCESS.2025.3545490.
[4] S. D. L. Shivaprasad, B. M. R. Bhavani, B. Fathima, and D. S. Guru, "Real-Time Animal Monitoring and Identification Using Deep Computer Vision," *Procedia Computer Science*, vol. 283, pp. 380–391, 2026, doi: 10.1016/j.procs.2026.06.124.
[5] D. C. Wilkins, K. M. Kockelman, and N. Jiang, "Animal-vehicle collisions in Texas: How to protect travelers and animals on roadways," *Accident Analysis & Prevention*, vol. 131, pp. 157–170, 2019, doi: 10.1016/j.aap.2019.05.030.