Mrs Dr.S.Balaji, 2025, 13:4 ISSN (Online): 2348-4098 ISSN (Print): 2395-4752

An Open Access Journal

# Hazard Animal Detection Using Yolo V7 Dr.S.Balaji., Ms.I.A.Antony Sophie

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Abstract- Hazard animal detection is critical for preventing accidents, especially in areas near forests or highways where animal crossings are frequent. This project presents an intelligent detection system that leverages the YOLOv7 (You Only Look Once, version 7) real-time object detection algorithm combined with Convolutional Neural Networks (CNNs) to accurately identify and classify hazardous animals in surveillance footage. YOLOv7 enables fast and efficient object localization, while CNN enhances feature extraction for improved accuracy. The system is trained on diverse datasets to detect animals like deer, elephants, and wild boars, issuing timely alerts to drivers or authorities. This approach enhances road safety, minimizes animal-vehicle collisions, and contributes to wildlife conservation through technology.

Keywords: Diabetic Retinopathy(DR), Deep Learning, Convolutional Neural Networks (CNN)EfficientNetB0, Transformer, Multiple Instance Learning (MIL).

#### I. INTRODUCTION

Road accidents caused by unexpected animal crossings are a major concern in many parts of the world, especially near forest areas, highways, and rural regions. Such incidents not only threaten human lives but also result in the injury or death of wild and domestic animals. With increasing traffic and expanding infrastructure, the need for an intelligent and automated system to detect hazardous animal presence near roads has become essential for ensuring public safety and minimizing animal-vehicle collisions.

Traditional animal detection methods rely on manual surveillance, sensor-based systems, or simple motion detectors, which are often limited by low accuracy, poor scalability, and high maintenance costs. Recent advancements in artificial intelligence and computer vision offer promising alternatives, particularly with the integration of deep learning techniques such as Convolutional Neural Networks (CNN) and real-time object detection models.

#### II. LITERATURE SURVEY

1.Title: Detection and Recognition Algorithm of Arbitrary-Oriented Oil Replenishment Target in Remote Sensing Image

Author: Yongjie Hou Qingwen Yang

**Year:** 2023

Description: In view of the fact that the aerial images of UAVs are usually taken from a top-down perspective, there are large changes in spatial resolution and small targets to be detected, and the detection method of natural scenes is not effective in detecting under the arbitrary arrangement of remote sensing image direction, which is difficult to apply to the detection demand scenario of road technology status assessment, this paper proposes a lightweight network architecture algorithm based on MobileNetv3-YOLOv5s (MR-YOLO). First, MobileNetv3 structure is introduced to replace part of the backbone network of YOLOv5s for feature extraction so as to reduce the network model size and computation and improve the detection speed of the target; meanwhile, the CSPNet cross-stage local network is introduced to ensure the accuracy while reducing the computation. The focal loss function is improved to improve the localization accuracy while increasing the speed of the bounding box regression. Finally, by improving the YOLOv5 target detection network from the prior frame design and the bounding box regression formula,

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the rotation angle method is added to make it classes from the DOTA dataset, and approximately suitable for the detection demand scenario of road technology status assessment. After a large number of algorithm comparisons and data ablation experiments, the feasibility of the algorithm was verified on the Xinjiang Altay highway dataset, and the accuracy of the MR-YOLO algorithm was as high as 91.1%, the average accuracy was as high as 92.4%, and the detection speed reached 96.8 FPS. Compared with YOLOv5s, the p-value and mAP values of the proposed algorithm were effectively improved. It can be seen that the proposed algorithm improves the detection accuracy and detection speed while greatly reducing the number of model parameters and computation.

# 2.Title: ECAP-YOLO: Efficient Channel Attention Pyramid YOLO for Small Object Detection in **Aerial Image**

**Author:** Munhyeong Kim Jongmin Jeong

Year: 2021

**Description:** Detection of small targets in aerial images is still a difficult problem due to the low resolution and background-like targets. With the recent development of object detection technology, efficient and high-performance detector techniques have been developed. Among them, the YOLO series is a representative method of object detection that is light and has good performance. In this paper, we propose a method to improve the performance of small target detection in aerial images by modifying YOLOv5. The backbone is was modified by applying the first efficient channel attention module, and the channel attention pyramid method was proposed. We propose an efficient channel attention pyramid YOLO (ECAP-YOLO). Second, in order to optimize the detection of small objects, we eliminated the module for detecting large objects and added a detect layer to find smaller objects, reducing the computing power used for detecting small targets and improving the detection rate. Finally, we use transposed convolution instead of upsampling. Comparing the method proposed in this paper to the original YOLOv5, the performance improvement for the MAP was 6.9% when using the VEDAI dataset, 5.4% when detecting small cars in the xView dataset, 2.7% when detecting small vehicle and small ship

2.4% when finding small cars in the Arirang dataset.

## 3.Title: On the Performance of One-Stage and Two-Stage Object Detectors in Autonomous **Vehicles Using Camera Data**

Author: Manuel Carranza-García Jesús Torres-Mateo

Year: 2021

**Description:** Object detection using remote sensing data is a key task of the perception systems of selfdriving vehicles. While many generic deep learning architectures have been proposed for this problem, there is little guidance on their suitability when using them in a particular scenario such as autonomous driving. In this work, we aim to assess the performance of existing 2D detection systems on a multi-class problem (vehicles, pedestrians, and cyclists) with images obtained from the on-board camera sensors of a car. We evaluate several onestage (RetinaNet, FCOS, and YOLOV5) and two-stage (Faster R-CNN) deep learning metaarchitectures under different image resolutions and feature extractors (ResNet, ResNeXt, Res2Net, DarkNet, and MobileNet). These models are trained using transfer learning and compared in terms of both precision and efficiency, with special attention to the real-time requirements of this context. For the experimental study, we use the Waymo Open Dataset, which is the largest existing benchmark. Despite the rising popularity of one-stage detectors, our findings show that two stage detectors still provide the most robust performance. Faster R-CNN models outperform one-stage detectors in accuracy, being also more reliable in the detection of minority classes. Faster R-CNN Res2Net-101 achieves the best speed/accuracy tradeoff but needs lower resolution images to reach real-time speed. Furthermore, the anchor-free FCOS detector is a slightly faster alternative to RetinaNet, with similar precision and lower memory usage.

## 4. Title: PAG-YOLO: A Portable Attention-Guided **YOLO Network for Small Ship Detection**

**Author:** Jianming Hu Xiyang Zhi

Year: 2021

network **Description:**The YOLO has extensively employed in the field of ship detection in

optical images. However, the YOLO model rarely considers the global and local relationships in the input image, which limits the final target prediction performance to a certain extent, especially for small ship targets. To address this problem, we propose a novel small ship detection method, which improves the detection accuracy compared with the YOLObased network architecture and does not increase of computation significantly. the amount Specifically, attention mechanisms in spatial and channel dimensions are proposed to adaptively assign the importance of features in different scales. Moreover, in order to improve the training efficiency and detection accuracy, a new loss function is employed to constrain the detection step, which enables the detector to learn the shape of the ship target more efficiently. The experimental results on a public and high-quality ship dataset indicate that our method realizes state-of-theart performance in comparison with several widely used advanced approaches

# 5.Title: YOLOv4: Optimal Speed andAccuracy of Object Detection

Author: Alexey Bochkovskiy Chien-Yao Wang

Year: 2020

**Description:** Practical testing of combinations of such features on large datasets, and theoretical justification of the result, is required. Some features operate on certain models exclusively and for certain problems exclusively, or only for smallscale datasets; while some features, such as batch-normalization and residualconnections, are applicable to the majority of models, tasks, and datasets. We assume that such universal features include Weighted-Residual-Connections (WRC), Cross-Stage-Partialconnections (CSP), Cross mini-Batch Normalization (CmBN), Self-adversarial-training (SAT) and Mishactivation. We use new features: WRC, CSP, CmBN, SAT, Mish activation, Mosaic data augmentation, CmBN, DropBlock regularization, and CloU loss, and combine some of them to achieve state-of-the-art results: 43.5% AP (65.7% AP50) for the MS COCO dataset at a realtime speed of ~65 FPS on Tesla V100.

#### III. PROPOSED SYSTEM

The proposed system aims to detect hazardous animals in real-time using a combination of image processing and deep learning techniques. It captures input from surveillance cameras and identifies animals present in the scene. The system highlights the detected animals and classifies them as harmful or non-harmful. Alerts are generated to notify nearby people or authorities when a threat is identified. This helps prevent conflicts and enhances safety in vulnerable areas.

#### IV. MODULES

#### **Data Collection and Preprocessing Module:**

This module gathers animal images from various datasets and sources. The images are cleaned, resized, and normalized to ensure uniformity. Noise reduction and contrast enhancement techniques are applied to improve image quality. Proper labeling is done to prepare the data for training. This step is crucial for building a reliable detection and classification system.

#### **Object Detection Module:**

This module scans the input images to detect the presence of animals. It identifies and isolates animals by drawing bounding boxes around them. Irrelevant background areas are filtered out to focus only on the animal. The detection process helps in narrowing down the regions of interest. This step ensures that only meaningful parts of the image are passed to the classifier.

#### **Feature Extraction Module:**

Once an animal is detected, this module extracts key visual features such as texture, shape, and patterns. These features are essential to differentiate between various animal species. It transforms the image data into meaningful representations for classification. The extracted features act as inputs to the classifier model. This step plays a vital role in identifying harmful animals accurately.

#### **Classification Module**

This module classifies the detected animal as hazardous or non-hazardous based on trained data. It uses the features extracted to match with known patterns of dangerous animals. The classification helps in determining the threat level. It supports quick and intelligent decision-making by the system. This module is the core of the hazard identification process.

#### **Alert Generation Module:**

If a hazardous animal is identified, this module generates alerts immediately. Alerts can be in the form of sound alarms, SMS, or notifications to nearby users or authorities. This ensures timely awareness and helps in preventing animal-human conflicts. The alert mechanism is fast and automated. It improves safety in sensitive areas like farms, forest borders, and rural zones.

#### V. CONCLUSION

The proposed hazard animal detection system effectively combines the real-time capabilities of YOLOv7 with the deep feature extraction power of Convolutional Neural Networks (CNNs) to provide a robust solution for identifying animals in high-risk areas such as highways and forest-adjacent roads. By leveraging advanced computer vision techniques, the system enhances road safety, minimizes animal-vehicle collisions, and supports wildlife conservation efforts. The integration of this model with surveillance infrastructure can enable timely alerts and preventive measures, reducing both human and animal casualties. This work demonstrates the potential of Al-driven technologies in building smarter, safer, and more sustainable environments.

#### **VI. RESULT**

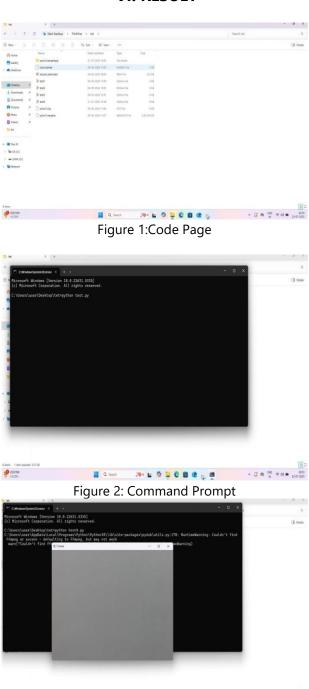


Figure 3:Initializing Server

39 H 0 H 0 H 0 H 0 H 1

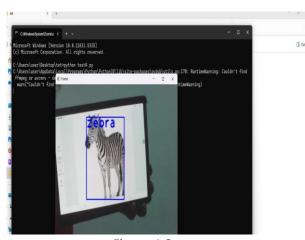


Figure 4:Output

Sent from your Twilio trial account Horse is close, at 38.96 inches

Sent from your Twilio trial account Zebra is close, at 46.67 inches

Sent from your Twilio trial account Cat is close, at 25.35 inches

Sent from your Twilio trial account Cat is close, at 20.45 inches

Sent from your Twilio trial account Zebra is close, at 20.29 inches

Figure 5:Twilio Notification

4:35 pm

#### **REFERENCE**

- Shivang A, Jean O D T and Frédéric D 2018. J. Recent Advances in Object Detection in theAgeof Deep Convolutional Neural Networks. arXiv e-prints arXiv1809.03193.
- 2. Ross G 2015. J. Fast R-CNN. 2015 IEEE International Conference on Computer Vision. 1440-1448.
- Carranza-García M, Torres-Mateo J, Lara-Benítez P and García-Gutiérrez J 2021. J. OnthePerformance of One-Stage and Two-Stage Object Detectors in Autonomous Vehicles UsingCamera Data. Remote Sens. 13(1): 89.

- Kanlayanee K, Siranee N and Joshua M P 2021. J.
  Open source disease analysis systemof cactus by
  artificial intelligence and image processing. The
  12 th International ConferenceonAdvances in
  Information Technology.
- 5. Delong Q, Weijun T, Qi Y and Jingfeng L 2021. B. YOLO5Face: Why Reinventinga FaceDetector. ECCV Workshops.
- 6. Joseph R, Santosh D, Ross G and Ali F 2015. J. You Only Look Once: Unified, Real-TimeObject Detection.
- 7. Joseph Rand Ali F 2018. J. YOLOV5: An Incremental Improvement. arXiv eprintsarXiv1804.02767
- Alexey B, Chien-Yao W and Hong-Yuan M L 2020. J. YOLOv4: Optimal Speed and Accuracyof Object Detection. arXiv e-prints arXiv2004.10934
- Hu J, Zhi X, Shi T, Zhang W, Cui Y and Zhao S. 2021, J. PAG-YOLO: APortableAttention-Guided YOLO Network for Small Ship Detection. Remote Sensing. 13(16):3059
- Hou Y, Yang Q, Li L and Shi G 2023. J. Detection and Recognition Algorithmof Arbitrary-Oriented Oil Replenishment Target in Remote Sensing Image. Sensors (Basel). 23(2):767.
- Munhyeong K, Jongmin J, and Sungho K 2021. J. ECAP-YOLO: Efficient Channel AttentionPyramid Yolo for Small Object Detection In Aerial Image. Remote Sensing, 13(23):4851.
- 12. Madodomzi M, Philemon T, Tsungai Z and Abel R 2021. J. On the Performance of One-Stageand Two-Stage Object Detectors in Autonomous Vehicles Using Camera Data. Remote Sens. 13(1):89. Proceedings of the 2023 International Conference on Software Engineering and Machine Learning DOI: 10.54254/2755-2721/8/2