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Deep Learning for Hazardous Animal Detection Integrated with Blynk IOT for Real-Time Alerts

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ABSTRACT

Animal-related concerns to human safety and agriculture include cattle incursions and collisions between wildlife and vehicles. In order to reduce these hazards by real-time identification and monitoring, this research investigates the application of deep learning approaches for danger animal detection. The system can identify and categorize animals in a variety of settings, such as protected areas, farms, and roadways, by using Convolutional Neural Networks (CNNs) on visual data. This strategy offers an effective way to manage animal hazards while improving safety, minimizing damages, and assisting with wildlife conservation initiatives. A large dataset of animal species is used to train the deep learning model, which then uses predictive analytics to predict movement patterns. This enables prompt warnings and preventative actions, including turning on automated barriers or warning systems. Through smooth communication and remote control through mobile devices made possible by the connection with Blynk IoT, stakeholders may effectively monitor and manage threats. In order to improve detection accuracy in difficult circumstances, such as poor visibility or inclement weather, the system also makes use of Internet of Things-enabled sensors, such as cameras, motion detectors, and thermal imaging. Farmers, road authorities, and animal conservationists all gain from the design's scalability and ease of use, which guarantees adaptability to various geographies and uses. This technology provides a proactive way to reduce agricultural losses, improve safety, mitigate animal-related hazards, and foster human-wildlife cohabitation by fusing deep learning and IoT technologies.

Keywords: Real-Time Monitoring, Animal Detection, Deep Learning, Real Time Alerts, Blynk App.

I INTRODUCTION

The safety of people, agriculture, and biodiversity are all seriously threatened by animal-related threats, such as collisions between wildlife and vehicles and livestock invasions. Injuries, fatalities, economic losses, and disturbances to natural ecosystems are all outcomes of these catastrophes. Since these occurrences are becoming more frequent, creative ways to identify and successfully reduce these risks are desperately needed. When it comes to managing hazards in real time, conventional techniques like physical barriers and manual monitoring are frequently insufficient. New developments in the Internet of Things (IoT) and deep learning provide encouraging answers. Convolutional Neural Networks (CNNs), in particular, enable deep learning to accurately identify and classify animals in a variety of settings, including protected areas, farms, and roadways. Deep learning can be used to train models to identify various species and forecast their movement patterns, enabling preemptive actions to stop mishaps and harm. Deep learning combined with IoT technologies improves the system's real-time capabilities. Animal activity may be continuously monitored thanks to Internet of Things devices like cameras, motion detectors, and temperature sensors, which can also set off instantaneous reactions like automated barriers or alerts. Remote control and management of these systems is made feasible by platforms such as Blynk IoT, which guarantee that stakeholders may receive timely notifications and take the necessary steps from any location. This IoT and deep learning combo provides a complete solution for dangerous animal detection. By lowering the number of accidents, it not only increases safety but also helps agriculture by keeping cattle out of the way and safeguarding crops. Additionally, it is essential for wildlife protection because it offers non-intrusive monitoring in protected regions. For both people and wildlife, this method helps create a more secure and sustainable environment by providing a scalable, effective, and real-time system.

II METHODOLOGIES OF HAZARDOUS ANIMAL DETECTION

Hazardous Animal Detection can have more Methodologies they are;

- Data Collection
- Data Preprocessing
- Model Training and Validation

- Species Classification
- False Alarm Reduction
- User Interface and Reporting

1 Data Collection

A strong and diverse dataset should include a variety of animal species, environmental factors, and viewpoints. Camera traps capture images and videos of animals in their natural habitat using stationary cameras. Drones equipped with cameras provide aerial footage from hard-to-reach areas, while stationary surveillance devices collect data from urban and rural regions. Public databases, such as GBIF and iNaturalist, offer pre-existing datasets from research centers and institutions. Crowdsourcing allows the collection of images and videos from eco-tourists and citizen scientists, increasing species and location diversity. The dataset should contain high-quality images taken in different lighting conditions, terrains, and angles. Videos are essential to record continuous animal activity and behavior. Environmental data, including weather, time of day, and geographic details, add valuable context to the images and videos. Combining these diverse data sources improves the dataset's accuracy and comprehensiveness. This approach ensures a robust dataset for wildlife monitoring and research.

2 Data Preprocessing

To prepare the gathered data for use in a machine learning model, several key preprocessing steps are essential. Resizing images to a standardized dimension ensures compatibility with the model's input requirements. Normalizing pixel values by scaling them to a consistent range, such as 0 to 1, improves model performance and training stability. Dataset augmentation is another critical step, involving transformations like cropping, flipping, rotation, and adjusting brightness or contrast. These augmentations increase the dataset's size and diversity, helping the model generalize better to new data. Proper preprocessing enhances the quality of the dataset, reduces overfitting , and ensures the model can effectively analyze and interpret the input data.

3 Model Training and Validation

YOLOv7-based deep learning models are fast and accurate for image classification. The process starts with collecting and preparing a labeled dataset, divided into 70% training, 20% validation, and 10% testing. Images are preprocessed by resizing and normalizing to fit the model's input size. During training, fine-tune hyperparameters like learning rate, batch size, and epochs while using early stopping and regularization to prevent overfitting. Transfer learning with pretrained YOLOv7 weights improves performance by freezing initial layers and adjusting higher ones. Data augmentation techniques, such as flipping and rotation, enhance dataset diversity. Model evaluation uses metrics like accuracy, precision, recall, and F1-score. For faster inference and efficient deployment, apply model pruning and quantization. YOLOv7's versatility makes it ideal for real-time applications in industries like retail, healthcare, and autonomous systems.

4 Species Classification

Species-level categorization faces several challenges, including inequitable datasets where some species are underrepresented, leading to biased models. Solutions like oversampling, undersampling, and weighted loss functions can address this imbalance. Visually similar species can confuse models, but advanced methods like fine-grained classification or incorporating features like habitat and behavior can help. Low-quality or occluded images also pose difficulties, which can be mitigated through preprocessing techniques like image enhancement or using multi-modal inputs such as sound or motion data. Real-time inference is challenging on edge devices with limited processing power, but techniques like model pruning, quantization, and lightweight architectures can optimize performance. Accurate data annotation is crucial, as labeling errors can reduce model accuracy, and large-scale annotation can benefit from crowdsourcing or semi-supervised learning. Environmental factors like seasonal behavior, time of day, and weather also affect detection, but incorporating contextual information such as timestamps and environmental sensors can improve model robustness and reduce false positives.

5 False Alarm Detection

Enhancing animal detection systems involves incorporating environmental context through sensors like weather and temperature to identify conditions that favor animal presence, such as increased nocturnal activity. Geofencing helps reduce false alarms by defining areas where animals are unlikely to appear. Time-based filtering analyzes detection patterns based on the time of day to identify unusual triggers. Behavioral analysis uses motion trajectory and speed to distinguish between animals, humans, and vehicles. Audio sensors can detect non-human sounds to complement visual detections, while infrared and thermal imaging filters out smaller animals by focusing on human-like size and heat signatures. Dynamic thresholding adjusts detection sensitivity in real time based on location or seasonal changes. Machine learning feedback continuously improves the system by using false alarm data, and multisensor fusion combines information from various sources like motion, thermal, and video to enhance detection accuracy.

6 User Interface And Reporting

Mapping wildlife locations involves using geocoordinated interactive maps to chart animal sightings and analyze species distribution over time. Time-based trends track animal activity across different times of the day, week, or year using time series graphs, while seasonal patterns visualize behavioral and movement changes across seasons. Density heatmaps highlight areas with high animal detection, and comparative visualizations use side-by-side charts to compare data across species, regions, or time periods. Real-time data dashboards provide live monitoring and decision-making capabilities. A user-centric design ensures these visualizations are accessible and easy to understand for both professionals and non-experts, such as environmentalists

III SYSTEM ANALYSIS

3.1 Existing system

Environmental factors like high, moving, or wet vegetation, wind, rain, water, fog, snow spray, and falling leaves can all affect how reliable animal detection systems are. False readings or missed detections may result from these circumstances. Large animals like deer, elk, and moose are the main targets of current technologies, which are less successful in spotting smaller ones. This restriction gives drivers a fictitious sense of security about tiny animals on or close to the road. False positives and negatives can result in missed detections or needless alerts, and this is especially true for both break-the-beam and area coverage systems.

3.1.1 Disadvantages

The main disadvantages of Existing System are

- **Overfitting and Model Complexity:** Overfitting is a problem that arises as models are more intricate in order to represent the subtleties of wildlife behavior and hazard identification. A model that learns the training data too well and performs badly on fresh, unseen data is said to be overfit.
- **Privacy Issues:** Detecting wildlife with cameras and sensors may cause privacy issues, particularly in places where wildlife is sensitive to human presence. It is essential to make sure that data gathering and analysis abide by privacy laws and regulations.
- **Environmental Impact:** The use of cameras and sensors can still affect wildlife habitats, even if machine learning can lessen the environmental impact of wildlife monitoring by reducing human presence. Environmental issues can also be exacerbated by data centers' energy usage and the processing of big databases.
- **False Positives and Negatives:** Reliability may be diminished by detection systems that mistakenly classify innocuous animals as threats (false positives) or miss real dangerous animals (false negatives).

3.2 Proposed System

In comparison to the original YOLOv3, ML-YOLOv3 drastically lowers the computing cost. It accomplishes this by incorporating a residual network design that is more effective. By reducing parameter sizes and floating point operations (FLOPs), this integration makes the model more appropriate for deployment on devices with constrained processing power. There is still a considerable detection effect with MLYOLOv3. Comparing the safety helmet dataset, the results show that it performs better than YOLOv3 in terms of detection accuracy. This shows that even with its decreased complexity, ML-YOLOv3 can still produce accurate detection results. In order to extract picture features, the system reworks the YOLOv3 multiscale feature extraction network by integrating depth-wise separable convolution. In addition to lowering the computational expense, our method guarantees that the detection impact stays high. It is also useful for detecting objects of varying sizes because the multiscale feature extraction network produces feature maps of three different scales. Customization of the suggested method is possible to solve particular wildlife detection issues, such as different animal sizes and forms. By properly utilizing the architecture, this customisation improves the system's capacity to distinguish between different animal species and adjust to geometric changes in their appearance.

3.2.1 Advantages

The Advantages of Proposed System are

- **Real-Time Warnings to Avoid Collisions:** When dangerous animals are in the area, hazardous animal detection systems instantly notify people so they may take precautions and stay safe.
- **Preservation of Endangered Species and Their Habitats:** These systems help to preserve endangered species and their natural habitats, fostering biodiversity, by identifying dangerous creatures without endangering people.
- **Reduction of Animal-Vehicle Collisions:** By alerting drivers to the presence of animals on the road, detection technology can lower the likelihood of collisions, improve road safety, and shield both people and animals from injury.

IV LITERATURE SURVEY

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

Author: Yingjie Hou Qingwen Yang

Year: 2023

This paper suggests a lightweight network architecture algorithm based on MobileNetv3-YOLOv5s (MR-YOLO) which is difficult to apply to the detection demand scenario of road technology status assessment because aerial images of UAVs are typically taken from a top-down perspective, which results in large changes in spatial resolution and small targets to be detected. Additionally, the detection method of natural scenes is ineffective when the remote sensing image direction is arbitrary. In order to decrease the size of the network model and computation and increase the target's detection speed, the MobileNetv3 structure is first introduced to replace a portion of the YOLOv5s backbone network for feature extraction. In the meantime, the CSP Net cross-stage local network is introduced to guarantee accuracy while lowering computation. To increase the speed of the bounding box regression and improve the localization accuracy, the focus loss function is enhanced. Lastly, the rotation angle approach is incorporated to the YOLOv5 target detection network to improve it from the previous frame design and the bounding box regression formula, making it appropriate for the detection demand scenario of road technology state assessments. The Xinjiang Altay highway dataset was used to confirm the algorithm's viability following numerous algorithm comparisons and data ablation experiments. The MR-YOLO algorithm's accuracy reached 91.1%, its average accuracy reached 92.4%, and its detection speed reached 96.8 frames per second. The suggested algorithm significantly improved the p-value and map values when compared to YOLOv5s. As can be observed, the suggested technique significantly lowers the number of model parameters and computation while increasing detection speed and speed.

2 Ecap-Yolo: Efficient Channel Attention Pyramid Yolo for Small Object Detection in Aerial Image

Author: Munhyeong Kim Jongmin Jeong

Year: 2021

Small targets in aerial photos are still challenging to detect because of their poor resolution and background-like appearance. As object detecting technology has advanced recently, effective and high-performing detector methods have been created. One of the best and most lightweight object detecting techniques among them is the YOLO series. This research suggests a way to alter YOLOv5 in order to enhance the performance of small target recognition in aerial photos. The channel attention pyramid method was devised, and the first effective channel attention module was applied to modify the backbone. We suggest ECAPYOLO, an effective channel attention pyramid YOLO. Second, we removed the large object detection module and created a detect layer to locate smaller objects in order to maximize the identification of tiny objects. This improved the detection rate and reduced the amount of computational resources required for small target detection. Lastly, rather than using up sampling, we employ transposed convolution. Using the VEDAI dataset, the performance improvement for the map was 6.9%; detecting small cars in the x View dataset, 5.4%; detecting small vehicle and small ship classes from the DOTA dataset, 2.7%; and finding small cars in the Arirang dataset, roughly 2.4%, when comparing the method presented in this paper to the original YOLOv5.

3 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

Object detection using remote sensing data is a key task of the perception systems of self-driving vehicles. While many of the 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 one-stage (Retina Net, FCOS, and YOLOv3) and two-stage (Faster R-CNN) deep learning meta-architectures under different image resolutions and feature extractors (Res Net, Res NeXt, Res2Net, Dark Net, and Mobile Net). 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 Retina Net, with similar precision and lower memory usage.

4 Pag-Yolo: A Portable Attention-Guided Yolo Network for Small Ship Detection

Author: Jianming Hu Xiyang Zhi

Year: 2021

The YOLO network has been widely used in the field of optical image ship detection. Unfortunately, the YOLO model rarely takes into account the local and global relationships present in the input image. This restricts the final target prediction performance, particularly for tiny ship targets. In order to solve this issue, we provide a brand-new small ship identification technique that raises detection accuracy while requiring less processing than the YOLO-based network architecture. In order to adaptively assign the significance of features in various scales, attention mechanisms in spatial and channel dimensions are specifically presented. Additionally, to increase training efficiency and detection accuracy, a novel loss function is used to confine the detection step. This makes it possible for the detector to understand the ship target's shape more effectively. Comparing our method to a number of popular advanced approaches, the experimental findings on a high-quality ship dataset show that it achieves state-of-the-art performance.

5 Yolov4: Optimal Speed and Accuracy of Object Detection

Author: Alexey Bochkovskiy Chien-Yao Wang

Year: 2020

Convolutional neural networks (CNNs) are stated to have an increased accuracy due to a vast array of features. It is necessary to test these feature combinations in practice on sizable datasets and provide theoretical support for the findings. Some aspects, like batch-normalization and residual-connections, are suitable to most models, tasks, and datasets, while others only work on specific models, for specific issues, or on small-scale datasets. Such universal properties are assumed to include Mish-activation, Weighted Relative Connections (WRC), Cross-Stage-Partial-connections (CSP), Cross mini-Batch Normalization (CmBN), and Self-adversarial-training (SAT). Approximately 65 frames per second in real time on the Tesla V100. In order to attain state-of-the-art results, we combine a few of the new features—WRC, CSP, CmBN, SAT, Mish activation, Mosaic data augmentation, CmBN, Drop Block regularization, and CIoU loss—to obtain 43.5% AP (65.7% AP50) for the MS COCO dataset at a real-time speed of about 65 FPS on a Tesla V100.

V CONCLUSION

The Blynk IoT platform and deep learning are combined in this study to create an effective dangerous animal detection system. Convolutional neural networks (CNNs) are used in the suggested model to precisely identify harmful animals in real time. The technology improves safety precautions by giving users immediate alerts through integration with Blynk. Rapid detection is ensured by the technology, lowering human dangers in places where wildlife is common. Decision-making and reaction times are enhanced by its real-time processing capabilities. Mobile devices can be used for remote monitoring and control thanks to IoT integration. The model's excellent accuracy indicates how well deep learning works for image-based animal detection. The automatic alert system improves security by sending out alerts instantly. This solution is scalable, reasonably priced, and environment-adaptable. With more varied datasets and sophisticated architectures, further research can increase detection accuracy. By using edge computing, latency can be decreased and speed increased. The system can be strengthened even more by adding capabilities like thermal imaging and audio-based detection.

VI Future Enhancement

Enhancements for hazardous animal detection in the future can concentrate on increasing model accuracy through training on a variety of datasets and using edge computing for quicker real-time processing. While multi-sensor fusion, which includes audio-based detection, can lower false positives, incorporating thermal and infrared imaging will improve detection in low light. AI-enabled autonomous drones can increase monitoring, and GPS-tracking geofencing can assist in predicting animal movements. Predictive analytics with AI will enhance threat assessment, and automatic deterrent can be achieved by integration with smart fencing. Additionally, a community-based alert system and a mobile app with interactive maps can improve real-time reporting and user interaction, increasing the system's flexibility and efficiency.

VII REFERENCES

1. Shivang A, Jean O D T and Frédéric D 2018. J. *"Recent Advances in Object Detection in the Age of 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.
3. Carranza-García M, Torres-Mateo J, Lara-Benítez P and García-Gutiérrez J 2021. J. *"On the Performance of One-Stage and Two-Stage Object Detectors in Autonomous Vehicles Using Camera Data. Remote Sens"*. 13(1): 89.
4. Kanlayanee K, Siranee N and Joshua M P 2021. J. *"Open source disease analysis system of cactus by artificial intelligence and image processing. The 12 th International Conference on Advances in Information Technology"*.
5. Delong Q, Weijun T, Qi Y and Jingfeng L 2021. B. YOLO5Face: *"Rein ventinga Face Detector. ECCV Workshops"*.
6. Joseph R, Santosh D, Ross G and Ali F 2015. J. *"You Only Look Once: Unified, Real-Time Object Detection."*
7. Joseph Rand Ali F 2018. J. *"YOLOv3: An Incremental Improvement"*. arXiv e-printsarXiv1804.02767