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Smart Surveillance System for Intrusion Detection and Environmental Hazard Monitoring

[1]Prathmesh Baviskar, [2]Joshua Dabhi, [3]Tejal Anavekar, [4]Sujal Raina, [5]Shubhangi Vaikole
[1]UG Student, [2]UG Student, [3]UG Student, [4]UG Student, [5]Professor
[1]Information Technology,
[1]Fr. C. Rodrigues Institute of Technology, Vashi, Navi Mumbai, India

Abstract: The Smart Surveillance System for Intrusions Detection and Environmental Hazard Monitoring is a remarkable improvement on the safety issues which is a great need for the overall security solutions which are prone to wildlife intrusions in residential areas. This high-end framework is set to utilize the latest in artificial intelligence, machine learning, and sensor technologies to ensure the timely detection of leopards that have become one of the major threats to security and safety. The system optimizes its performance through the meticulous fine-tuning of transfer learning utilizing the latest state-of-the-art machine learning algorithms of YOLOv8 to achieve high precision and reliability in leopard detection. The system that identifies a hazard will activate the alert immediately by means of buzzers with the aim of giving a prompt warning to the town's residents. The main function of the system is to build a false alarm free one and at the same time optimize resource utilization for both security and efficiency. The surveillance system can deal with the twofold threat of security breaches and environmental threats, and by doing so it not only protects the community but also reduces conflicts with wildlife. Through the using of state-of-the-art technology and strategic planning, it goes beyond what is already done in security, giving a hope for safer and more sustainable future in dangerous areas.

***Index Terms* - Leopard Detection, Machine Learning, SSD, YOLOv8.**

I. Introduction

The smart surveillance system is a high–end framework that has been specially developed to monitor residential areas with a first and foremost attention to detect the presence of leopards on entry. The motivation behind this research stems from the escalating frequency of security breaches, thefts, and illegal entries in various settings, including homes, businesses, and public areas. There is an urgent need for advanced surveillance systems capable of promptly identifying intrusions. Recent advancements in artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), and sensor technology present an opportunity to develop intelligent surveillance systems capable of multitasking. This initiative is inspired by the pressing need to create comprehensive surveillance solutions that not only enhance security but also protect the environment and address contemporary challenges.

This method incorporates the use of machine learning algorithms such as YOLOv8 and SSD which had been fine-tuned through the transfer learning approaches using the dedicated leopard dataset. By the means of diligent trial and error, YOLOv8 came up on the scene as the most efficient model, while its performance was remarkable with respect to accuracy and dependability. Upon sensing a leopard within the area which is under surveillance, the system immediately activates alerts that can warn local people living in that vicinity. The system is activated by buzzers which are a highly effective way of instantly and unambiguously alerting of the intrusion. Through the utilization of advanced machine learning algorithms, the platform targets to minimize the number of false alarms at the same time it seeks to ensure the optimal use of the resources.

This dual purpose is essential to the heightened security and efficiency of the surveillance system and is especially useful in dealing with the dangers posed by leopard invasions in residential areas. In addition to incorporating cutting-edge technology and optimization tactics, this project aims to tackle the urgent problem of the lack of appropriate surveillance systems in areas where wild animals are often observed. The smart surveillance system which gives out timely and correct alerts is a critical contributor in the security and safety of residents in the area. As a result, this will also reduce conflicts with wildlife. Additionally, it becomes possible to optimize resource allocation with the system, which helps to improve the efficiency of the processes and to reduce the cost-effectiveness to the desired extent.

The Smart Surveillance System for Intrusion Detection and Environmental Hazard Monitoring is an important step ahead in the development of out-of-the-home surveillance. Its usage of the state-of-art machine learning algorithms for reducing the false alarms and allocating resources is the critical tool that makes it a key to eliminate the environmental hazard effects.

II. Literature Survey

The approach outlined in the paper [1] utilizes a combination of computer vision and machine learning techniques for real-time wildlife intrusion detection and issuing alerts, with a specific focus on mitigating economic risks posed by wildlife, particularly wild boars. While the system offers an innovative and cost-effective solution, the article highlights potential challenges such as internet interruptions and limitations associated with free cloud storage. To address these challenges, the proposed project combines similar computer vision and machine learning methodologies, ensuring the timely delivery of alerts to farmers via SMS and email. By prioritizing local storage solutions and optimizing internet connectivity, the project aims to overcome the drawbacks associated with cloud-based solutions, thereby enhancing the reliability and performance of the intrusion detection system. This approach not only addresses the limitations mentioned in the article but also improves the overall effectiveness and robustness of the system in safeguarding agricultural fields from wildlife-induced damage.

The paper [2] drafts an automated villa smart alert system that focuses on improved security through integrating IoT. It provides the system with sensors, infrared cameras, and location detection APIs that help minimize false alarms. However, it points the way to technical and aesthetic enhancements to make it even better. The concept of the project resolves these challenges through the joining of the IoT systems for intrusion detection, which aims to differentiate among various entities and the reduction of the false alarms. Through the implementation of the smartly installed gadgets and utilizing cloud services for data saving and updating, this project enables the system to be both technically functional and enhanced in the user experience.

The paper [3] presents a new approach for animal detection which is mainly of interest in the case of the endangered species like the Himalayan bear, Marco Polo sheep and snow leopard. Yes, it does prove high accuracy with deep learning methods but it stresses on the need of localization of animals with a larger dataset. This project develops the strategy further by implementing the same deep learning and computer vision techniques to spot wildlife, particularly leopards, in residential areas, as the main concern. Through the use of the convolutional neural networks and classifiers, the system attempts to provide high accuracy detection of leopard intrusions, whilst taking into consideration the constraints of limited datasets and localization accuracy. By constantly improving the framework and conducting new trials, the aim is to make this framework contribute more effectively to wildlife monitoring and conservation activities.

The main objective of the project [4] is to eliminate human-wildlife conflicts by implementing an overall monitoring system in the field that would include sensors and cameras, which are designed to detect and classify intruders through a process of image processing. Yet, the attributes of such technology are in the fact that it may exhibit inaccuracies and it may also have the problems of scaling up of intruder classification by means of image processing techniques alone. This challenge is overcome by our project through using the best of machine learning models, especially YOLOv8 and SSD, trained on a data set images of various wildlife species, including leopards, as our training data. Our system learns and fine-tunes itself on the sample leopard dataset and thus becomes more proficient in detecting and classifying an unwanted intrusion, primarily leopards, as and when it happens in real-time. Furthermore, the integration of real-time alerting and response actions guarantees immediate and appropriate actions on the detection of leopard trespass, making a feasible solution to the permanent risk of human-wildlife conflicts in places where this conflict is a problem.

The research paper [5] is focused on marine animal find in coral reefs, with great importance for ecosystem conservation and support for AUV projects. Although the deep learning networks models, especially the YOLO algorithm, have revealed their potential in the rapid and precise recognition of the species of the marine animals, the implementation of the method still has some limitations. They can include, for instance, problems in handling different marine animals, varieties in underwater environments, and possibilities of false detections. For this project we address these challenges by using transfer learning techniques for YOLO model fine-tuning adapted to a wide sample of marine animal images taken at the coral reef environment. Our project generates transfer learning, which results in better generalization of the models across various marine species and in changing underwater conditions, thus ensuring better precision and smaller proportion of false positives. On top of that, the study results serve as a guidance for further model improvements, and thus contribute to the ongoing development in the field of marine animals' detection technology.

The study [6] introduces the Digital Borders technology that is based on the Computer Vision and Deep Learning techniques and is designed to locate animals in the border areas of the nature-sensitive sites. The method relies on distributed, cost-saving, and high-efficient components, with special attention to the inter-camera tracking of individuals. The above-mentioned design is able to generate good detection and re-identification results from many different animal species. The main shortcomings are the difficulties that may arise when trying to scale the system for large-scale deployment and the challenges of guaranteeing that the system maintains an appropriate level of performance under different environmental conditions. In this project, we confront these shortfalls by using highly sophisticated machine learning approaches including transfer learning, ensemble methods, and deep networks for detection and identification that work across multiple environments and animal species. Through detailed model tuning on the datasets related to the target deployment region and with an efficient system architecture for the scalability and robustness we are attempting to tackle the issues as the described research and will present an efficient solution to reduce human-animal conflict.

III. METHODOLOGIES

3.1 OpenCV

OpenCV [7], an open-source and complete toolkit, is referred to as the widely used and indispensable thing for the real-time computer vision software. It is a wide range of tools, algorithms, and functions that include various degrees of tasks. This toolkit is designed to handle many image and video analyzing actions. OpenCV gets used by the industries and the research areas widely and the applications which are based on object detection and recognition find its utility in a variety of cases, like, facial and gesture recognition. Although the main role of this tool is just image processing, its capabilities go much further, as it is also reinforced with machine learning, empowering developers to successfully cope with complex tasks. As an open-source library, OpenCV has a very thoughtful architecture that proffers real-time applications' moments to work in numerous spheres such as robotics and healthcare.

3.2 SSD

SSD (Single Shot Detector) [8] is the new cutting-edge technique that gave a single-stage design which does object detection and classification in a single neural network run. On a completely different level from the traditional methods in which the detection and classification tasks are carried out in a sequential manner, the SSD does the job in one step where it predicts the multiple bounding boxes along their associated class probabilities all at once for different scales and aspect ratios. This is implemented by the convolutional layers with a resolution decrease in a progression, which lets SSD to grasp different objects in different sizes and shapes. The main reason behind this is the exclusivity of this function that makes it very important in real-time applications such as autonomous driving and surveillance systems where rapidity and precision are the top priorities. SSD's adaptability and efficiency are reasons why it is a top-ranked technology among a variety of applications in computer vision, such as object recognition in both images and videos.

3.3 YOLOv8

YOLOv8 [9] which is the latest version in the line of successful YOLO (You Only Look Once) model series for object detection is the latest one in this series. YOLOv8 builds on the original YOLO version as it works on a single pass and detects the entire image at once and directly outputs bounding boxes and beliefs of classes. This approach gives users an impeccable level of speed and enables them to employ this YOLOv8 on the devices with the resource demands, thus the real-time performance is achieved. The YOLOv8 has several structure improvements and training strategies that are aimed at having both efficiency and accuracy. Here the term "improvements" refers to the integration of the backbone networks consisting of advanced backbone, feature pyramid networks, and new loss function. YOLOv8 is flexible and can be configured for multiple uses, including but not limited to surveillance, object tracking, and industrial automation. Realization of real-time objects with high precision is one of the reasons why users prefer it for the tasks the require the urgent decision making like video analytics and live monitoring systems.

IV. Implementation Details

The proposed system aims to safeguard residents in housing societies vulnerable to wild animal intrusions, particularly leopards. This system uses real-time object detection to trigger immediate alerts upon leopard identification within the society's premises.
The system continuously captures real-time video footage from cameras installed throughout the housing society. Upon detecting a leopard within a captured frame, the system activates a pre-configured alert mechanism that involves a buzzer to warn residents and deter the leopard.
Project focuses on suburban areas known for frequent leopard sightings and human-wildlife conflicts, the system is designed with the various considerations such as cameras strategically positioned to cover high-risk zones and potential entry points for leopards. The alert system can be customized to accommodate specific needs of housing society.

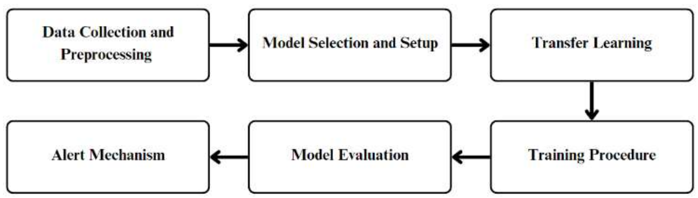

Fig. 1 Workflow of the system

4.1 Dataset Collection and Preprocessing

The study implemented a dataset designed for leopard detection inside housing societies. A thorough process of fieldwork and data collection was undertaken. Consequently, a variety of pictures and videos of leopard sightings were compiled. The dataset is carefully labelled which is essential for the model training. Bounding boxes were precisely placed around each leopard in the image to demonstrate the presence of leopard in every habitat. It is a carefully selected data set that consists of an array of pictures, which covers different lighting conditions, different backgrounds and the behavior of leopards. This diversity of setups is crucial for accurate training and testing of models to detect objects in real life conditions.

4.2 Model Selection

YOLOv8 and SSD, were selected as those most capable of identifying leopard intrusions because of their ability to accurately detect objects in images and videos, which makes them highly suitable for our surveillance system. A network architecture and hyperparameters were configured to meet our requirements such as adjusting the image size, anchor box configurations, and confidence thresholds to improve the detection accuracy.

4.3 Transfer Learning

The pre-trained weights from the models that were trained on datasets like COCO and ImageNet were used to start the training of our YOLOv8 and SSD models. This approach allowed us to start with models that already had valuable features for the general object detection task. Subsequently, the models were fine-tuned by using transfer learning techniques on the leopard dataset. This procedure enabled the model to grasp the leopard's unique traits while also capitalizing on the knowledge collected by the pre-trained weights. Therefore, the training process was accelerated, and the quality of the models was improved.

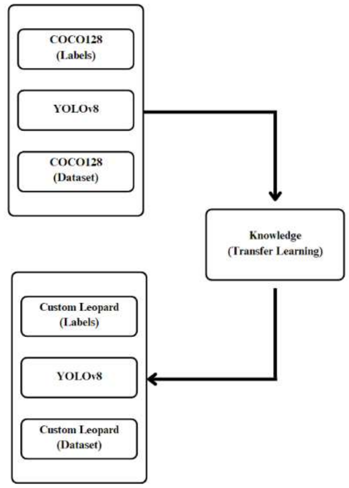

Fig. 2 Transfer Learning

4.4 Training Procedure

During the training process, the labeled dataset of leopards was fed into the YOLOv8 and SSD models, optimizing their parameters to minimize detection errors. Adam was used to optimize the models, with specialized loss functions for object detection tasks like bounding box regression and confidence loss. Key metrics including loss, precision, recall, and mean average precision (mAP) were monitored throughout training to evaluate performance and inform next steps. This iterative training method allowed the models to learn distinctive features of leopards and enhance detection accuracy with each epoch.

4.5 Model Evaluation

After training, YOLOv8 and SSD models were tested on a validation dataset to see how well they performed. The metrics like precision, recall, and mAP were observed to understand how accurate the models were detecting objects and how well they could generalize. The model's results were visually checked on sample images and videos to see if there were any mistakes, such as false positives or false negatives. This detailed evaluation helped to understand what the models were good at and where they could be improved. It also helped to figure out if any adjustments needed to be made.

4.6 Alert Mechanism

To improve the system's responsiveness and make sure that people are promptly informed about leopard intrusions, a notification system was added that will sound an alarm when a leopard is spotted in the area under surveillance. This alarm will not only warn residents about the possible danger but also deter leopards from moving further into residential neighborhoods. When a leopard is detected, the alert sound will go off, informing residents quickly so that they can take necessary steps to protect themselves and their surroundings.

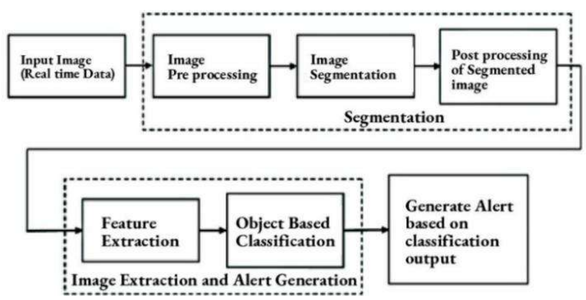

Fig. 3 Block Diagram

Block Diagram:

- Input Image: The source of the images that the system will work with, indicating that data is captured in real-time possibly from a camera or a video stream.
- Pre-Processing: This phase prepares the image for further processing, which may include tasks like reducing noise, enhancing contrast, or resizing it to a standard format for the model.
- Segmentation: Partitioning the image into meaningful regions or objects. In the case of leopard intrusion detection, it means identifying regions containing potential leopards.
- Image Extraction of Segmented Image: Extracting specific image regions of interest based on the segmentation results.
- Feature Extraction: In this stage, goal is to identify and extract specific characteristics from different parts of the image. These characteristics play vital role in categorizing objects.
- Object-Based Classification: In this step, a model for classifies objects (trained on a collection of images of leopards) examines the extracted features to figure out if there are leopards present in the image.
- Generate Alert Based on Classification Output: If the classification process identifies a leopard with a high level oof certainty, an alert is triggered.

System Workflow:

1. Capture real-time data: This step captures real-time data, which refers to images or video footages from a camera.
2. Analyze the Input Data: The captures data is then analyzed to identify the leopards in the frame.
3. Check if any intrusion detected: This step checks if any intrusion has been detected in the data frames.
4. Is intrusion a leopard: If an intruder is leopard, this step determines whether the animal is leopard. This involves use of image recognition and classification methods.
5. Raise an alert: An alert is raised if intrusion is detected and intruder is a leopard.
6. No alert will be raised: If no intruder is detected, or if an intruder is not leopard, then no alert will be raised and the process ends.

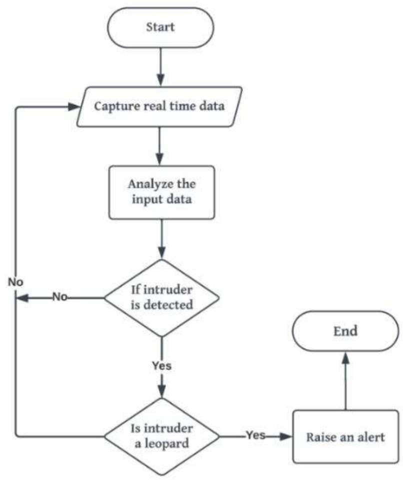

Fig. 4 Flowchart

V. Result

By thoroughly testing detection models, conducting real-world tests, and gathering user input, we evaluated how well our system can reduce the risks of leopard intrusions. We first analyzed how well the YOLOv8 and SSD models can detect leopard sightings, comparing them by looking at various factors such as mean average precision (mAP), various loss functions, determining losses in different scenarios. We then assess how quickly the alert system informs residents about leopard intrusions and review the outcomes of real-life tests to confirm the system's effectiveness.

5.1 YOLOv8

Model demonstrated strong performance on precision and recall. It showed impressive results achieving a Box Precision (P) of 0.879 and Recall (R) of 0.845. These metrics indicate that around 87.9% of the predicted bounding boxes matched up with leopard instances, and about 84.5% of the actual leopard instances were correctly classified by the model. Despite training model on constrained environment with limited computational resources and dataset availability, results showcase strong performance in challenging conditions.

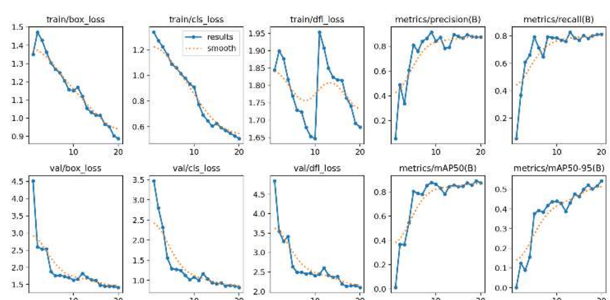

Fig. 5 Evaluation metrics (YOLOv8)

Model achieved an outstanding mean Average Precision (mAP50) of 0.908 at an Intersection over Union (IoU) threshold of 0.5. Model showcased very good computational efficiency, with fast inference speed averaging 11.0 milliseconds per image. This time includes preprocessing (0.4ms), inference (11.0ms), and postprocessing (6.3ms) per image.

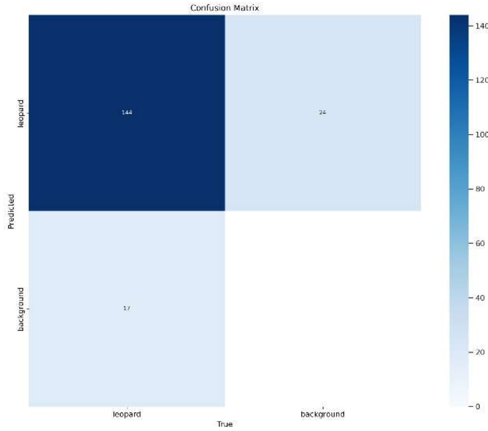

Fig. 6 Confusion matrix

5.2 SSD

Model showed an impressive performance on the dataset, with an average precision of 0.975 at an IoU threshold of 0.5 and an average precision of 0.611 across different IOU thresholds. The mean Average Precision for detection boxes was 0.61, with a notable mAP of 0.97 at an IoU threshold of 0.50.

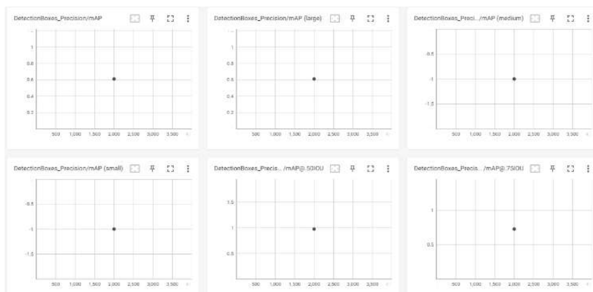

Fig. 7 Mean Average Precision (SSD)

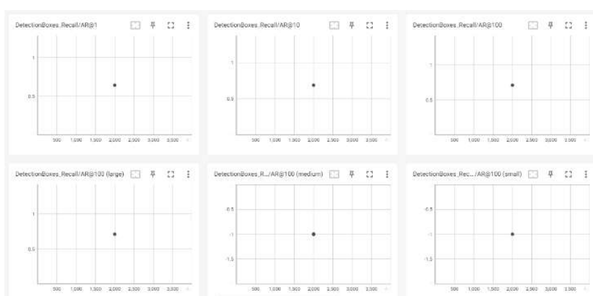

Fig. 8 Average Recall (SSD)

Fig. 9 Loss Function (SSD)

After evaluating various factors from the model summary of the YOLOv8 and SSD, it is found that while SSD had impressive performance with an average precision of (AP) of 0.975 at an Intersection over Union (IoU) threshold of 0.50 and AP of 0.611 across IOU threshold of 0.50 to 0.95, YOLOv8 showed even better accuracy metrics. YOLOv8 achieved a Box Precision (P) of 0.879 and a Recall (R) of 0.845, indicating superior precision and recall rates compared to SSD.

Moreover, the mean Average Precision (mAP) of YOLOv8, at an IoU threshold of 0.50, was 0.908, which outperformed SSD's mAP of 0.611. This indicates superior detection performance across various bounding box overlaps. Additionally, YOLOv8 demonstrated a fast inference speed of 10.7 milliseconds per image, making it ideal for real-time applications. Its consistent high performance in precision, recall, and mAP metrics, combined with its efficient inference speed, made YOLOv8 the preferred option for our project's needs.

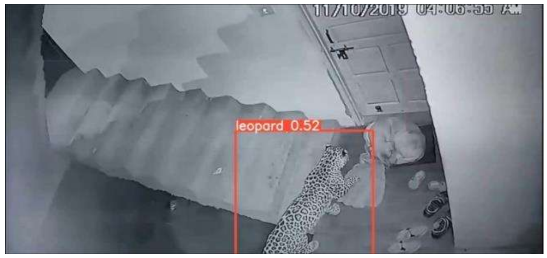

Fig. 10 Leopard Intrusion Detection

VI. Conclusion

The highly advanced surveillance system reflects a vital stage to ensure safety and reduce the negative aspects of wild animals invading the residential places. Utilizing on the latest machine learning algorithms and effective processing pipelines that allow real-time monitoring, the system had great ability in sensing leopard incursions and notifying residents immediately. The reliable detection and tracking of animals in real-time combined with the notification and the allocation of resources to the right places demonstrate the system's capability for addressing the contemporary intrusion detection and environmental hazard monitoring issues. From now on, the remaining tasks and upgrades to be done will be taken into account to increase system performance, efficiency and usability which will eventually lead to the creation of a safer and more sustainable society.

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