Wild Animal Detection and Alert System Using YOLOv5 and WhatsApp Notification

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ABSTRACT

This initiative addresses the pressing need for monitoring wildlife in real-time within border regions of jungle areas and forest reserves to mitigate potential human-wildlife interactions and enhance conservation efforts. A Python-based system has been developed that integrates computer vision and instant messaging technologies for the autonomous identification of animals and notification. The core of the system utilizes the pre-trained YOLOv5 object detection model, which has been trained on an extensive dataset, to identify specific animal species within its viewing area. To optimize detection for its particular use case, the model's confidence threshold has been adjusted to 10%, thus enhancing its sensitivity. The system is designed to identify a specified set of animal classes relevant to the unique ecological context, as articulated in a YAML configuration file, allowing for adaptability across different geographical locations and conservation goals. A regular laptop camera captures live video, and the YOLOv5 model processes each frame to identify objects. The initial detection results are refined using a custom filtering function (filter_animals) to locate the specified animal categories. Upon identifying a target animal, the system promptly sends an alert via WhatsApp, employing the pywhatkit library to deliver a message to a designated recipient, such as village officials or forest rangers. This alert message specifies the type of animal that was detected. Additionally, the system provides visual feedback by showing bounding boxes around the identified animals on the video stream, which is presented in real-time using cv2. This visual aid allows for immediate verification of the detection. The settings, including the specific species of animals and the WhatsApp number of the recipient, are managed through an external YAML file, ensuring flexibility and simplicity in modifications. Early testing and initial deployment demonstrate the system's capability to promptly recognize and notify about the presence of targeted wildlife. This automated system offers a cost-effective and viable answer for continuous animal surveillance, allowing for preemptive measures to safeguard both humans and wildlife, while also offering valuable insights for conservation strategies. Future enhancements may explore the possibility of linking with remote camera networks, utilizing cloud processing, and developing sophisticated alert management systems.

1. INTRODUCTION:

The expansion of human communities into areas that were previously natural habitats, along with the increasing division of these environments, has led to a significant rise in conflicts between humans and wildlife globally. These conflicts manifest in various ways, including wildlife damaging crops, attacking livestock, and in severe instances, harming humans. Such encounters endanger both human safety and economic stability, particularly for rural communities located on the edges of forests, while also negatively impacting animal populations often leading to retaliatory killings and habitat destruction. Timely and effective measures are crucial to prevent these conflicts, protect human life and assets, and ensure the survival of at-risk animal species for the future.

This initiative aims to address these obstacles by developing a system that utilizes advancements in computer vision, especially in object detection, alongside real-time communication technologies. This will provide a swift and reliable method for identifying the presence of wild animals in or near human communities and restricted zones. The central idea is to create a system that continuously monitors a designated area, autonomously identifies specific animal species of interest, and promptly notifies important parties such as local councils, forest rangers, or wildlife conservationists about any findings. This proactive alert system enables timely measures to be implemented, such as dispatching rangers to the location, installing barriers to prevent animal intrusion, or alerting nearby residents, thereby minimizing the likelihood of conflicts and damage.

The system utilizes the YOLOv5 model for object detection, known for being both fast and highly precise in recognizing objects in images and video feeds. After training this model on an extensive collection of images featuring various animal species, the system is adept at accurately identifying diverse species, regardless of challenging environmental factors. The design of the system aims to be both geographically specific and ecologically relevant. Users can specify the animal species they are interested in within their locale through a configuration file, enabling the system to focus its detection efforts on the most pertinent threats. This adaptability is crucial, as the animals that pose a threat can differ significantly from one region of the world to another.

Furthermore, the initiative incorporates a real-time messaging feature that makes use of the widely-used WhatsApp app to send immediate alerts. Once an animal is identified, the system promptly transmits a notification to a designated recipient containing information about the species that has been located. This instant alert system facilitates quick responses and actions, minimizing the time lag between identifying animals and implementing necessary mitigation measures. WhatsApp was chosen as the communication method because of its widespread accessibility, ease of use, and reliability in delivering messages, even in areas with poor connectivity.

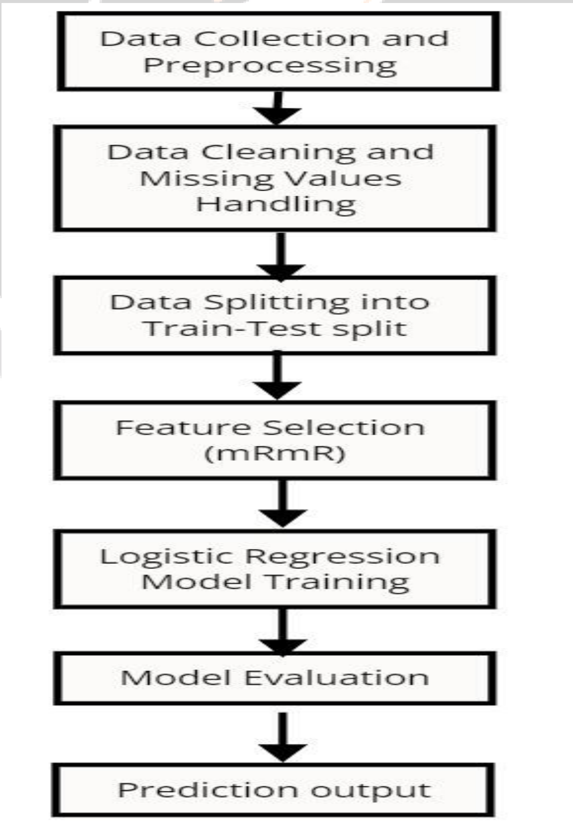


Fig 1. Flow Model

In addition to its real-time alert system, the platform provides a visual display that shows the video stream with bounding boxes around the detected animals. This visual verification allows users to check the accuracy of the detections and provides valuable insights into the animal's location and behavior. The visual feedback is beneficial for assessing the circumstances and making informed decisions on what actions to take. The goal of the system is to be a long-lasting contribution to both conservation efforts and human safety. By providing a reliable and swift method for identifying and responding to wildlife presence, it has the potential to reduce human-wildlife conflicts, protect endangered species, and promote harmony between humans and wildlife. Through providing an effective and reliable way to detect and respond to wildlife activity, it can help manage conflicts between humans and wildlife, protect endangered species, and promote harmony between the two. The created system is affordable, easily expandable, and simple to implement, which makes it well-suited for areas with limited resources and outdoor settings.

2. LITERATURE REVIEW

Human-animal conflict is a complex and worsening problem, particularly in regions where farming and human habitation encroach upon wildlife habitats. This type of conflict, driven by the destruction of natural environments, competition for resources, and rising human populations, necessitates the development of effective strategies to observe and address wildlife issues. This literature review examines past studies and wildlife detection methods, focusing on the use of computer vision, deep learning, and remote sensing techniques, along with the incorporation of communication technologies for immediate notifications. Building on this, Tan et al. (2023) advanced the idea by implementing attention-focused convolutional neural network (CNN) architectures for artist classification. Their research showed that by directing the model's focus on significant spatial elements in artworks, they achieved enhanced accuracy in artist identification.

Traditional Wildlife Monitoring Methods:

Traditionally, the observation of wildlife has relied heavily on established methods, which include:

• **Manual Surveys:** This method involves trained personnel conducting field observations to document the presence of animals, their tracks, and other indicators. While they offer valuable ecological insights, manual surveys can be labor-intensive, time-consuming, and have a limited geographical reach.

• **Camera Traps:** These devices are installed in remote locations and capture images or videos when triggered by motion or heat sensors. Camera traps have become a widely used tool in wildlife research and monitoring, allowing for non-intrusive data collection over extended periods. However, they require significant effort to set up, maintain, and retrieve data, and they do not provide immediate information.

- **Radio Telemetry and GPS Tracking:** These methods involve equipping animals with transmitters to monitor their movements and the areas they inhabit. Although they provide valuable insights into the actions of specific animals, they can be expensive, require the capturing and handling of the animals, and have constraints regarding battery lifespan and signal distance. Emerging Technologies for Wildlife Detection

Recent advancements in computer vision, deep learning, and sensor technology have created fresh avenues for automated and real-time detection of wildlife:

• **Computer Vision and Deep Learning:** Techniques in computer vision, particularly those based on deep learning, have seen notable achievements in the fields of object detection and image classification. Convolutional Neural Networks (CNNs), including models like YOLO (You Only Look Once), Faster R-CNN, and SSD (Single Shot MultiBox Detector), have been effectively employed to pinpoint different species of animals within images and video footage. These models can undergo training using extensive datasets of animal images to identify distinctive characteristics and accurately categorize animals in a variety of environments.

Computer Vision and Deep Learning: Techniques in computer vision, particularly those grounded in deep learning, have demonstrated great effectiveness in identifying objects and classifying images. Convolutional Neural Networks, such as YOLO (You Only Look Once), Faster R-CNN, and SSD (Single Shot MultiBox Detector), have been employed to recognize various animal species within images and videos. These models can be trained on extensive collections of animal imagery to learn distinctive characteristics that enable accurate identification of animals across diverse settings.

- **YOLO (You Only Look Once):** The YOLO series of models, including YOLOv5 which is used in this project, is known for its impressive speed and accuracy, making it ideal for applications that require real-time processing. YOLO models analyze the entire image at once, enabling rapid object detection.

- **Faster R-CNN (Region-based Convolutional Neural Network):** Faster R-CNN is a popular model for detecting objects that starts by suggesting areas of interest, followed by the classification and refinement of bounding boxes. While it tends to be more accurate than YOLO, it also requires more computational resources.
- **SSD (Single Shot MultiBox Detector):** The SSD serves as a one-step detector that simultaneously forecasts bounding boxes and class likelihoods from its feature maps. It strikes a good balance between performance and efficiency.

• **Heat Sensing:** Infrared cameras are capable of detecting the thermal emissions from animals, making them perfect for locating creatures in low-light conditions or dense foliage. The technology can be integrated with computer vision techniques to enhance the automated recognition and analysis of animals.

• **Sound Monitoring:** This technique involves setting up devices that record animal vocalizations and using signal analysis along with machine learning techniques to identify different species. Sound monitoring is particularly valuable for spotting elusive animals such as birds, bats, and amphibians.

• **Aerial Observation:** Satellite images and drone photography can be employed to track habitat alterations, observe animal migrations, and identify larger animals in open spaces. However, these methods have limitations in spatial resolution, making it challenging to spot smaller animals or those hidden in wooded areas.

Real-time Notification and Communication Systems:

In addition to animal detection, it is crucial to implement alert systems that notify relevant parties instantly. The communication technologies used to facilitate this consist of:

•**Radio Communication:** Traditional radio systems remain widely used in various scenarios for communication between personnel and control centers. However, they are limited in their range and are not particularly effective when it comes to transferring large amounts of data.

•**Cellular Networks:** Cellular networks provide broad coverage and can be employed to transmit data, including images and videos, from remote areas. These networks have been leveraged to develop mobile apps and online platforms aimed at wildlife monitoring and alerts.

•**Satellite Communication**: Satellite communication is essential for areas that lack sufficient cellular service. Systems that rely on satellites can transmit data from remote sensors and establish communication channels for staff working in the field.

• **Instant Messaging Apps:** Platforms like WhatsApp, Telegram, and similar applications deliver a fast and cost-effective means of sending immediate notifications and alerts. These apps are widely favored and come equipped with functions such as group messaging, location sharing, and support for multimedia content.

Integration of Technologies for Human-Wildlife Conflict Mitigation:

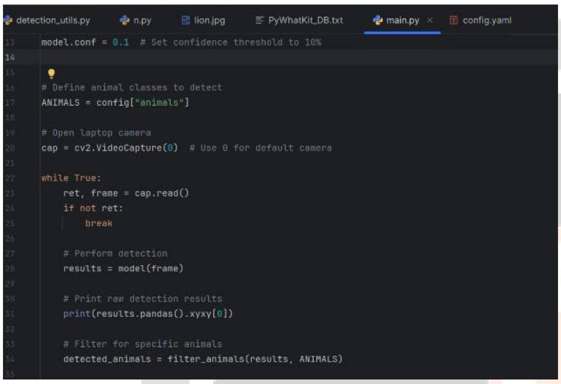
The integration of computer vision, deep learning, and communication technologies offers an effective approach to addressing conflicts between humans and wildlife. Systems that detect animals in real-time can provide timely warnings about their presence, enabling preemptive steps to be taken to prevent encounters and reduce potential harm. Additionally, these systems can supply valuable insights for wildlife studies and conservation efforts, aiding in informed management choices and protecting endangered species. This initiative contributes to this growing area by developing a system that utilizes the rapid and accurate capabilities of YOLOv5 alongside WhatsApp's real-time notification feature, presenting an affordable and practical option for monitoring wildlife and preventing conflicts in at-risk areas.

3. METHDOLOGY

This project employs a strategy that incorporates computer vision techniques, specifically through deep learning-based object detection, to identify wildlife in live video feeds and issue notifications. The main components of this approach include:

a. Data Gathering and Preparation (Implicit):

While this project does not involve traditional data cleaning typically associated with tabular datasets, it's essential to understand how video frames are processed and the training of the YOLOv5 model.



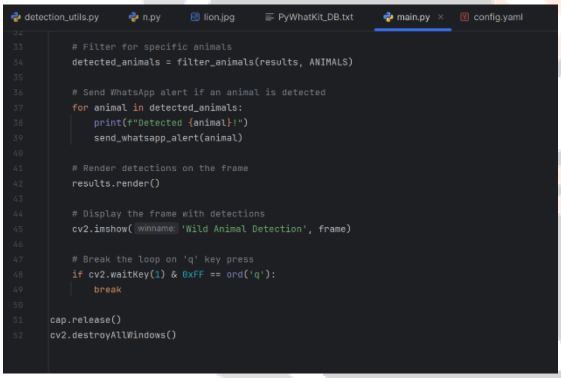


Fig1, Fig 2 : code for capturing data

• **YOLOv5 Training Data**: The pretrained YOLOv5 model used in this project has been developed using a vast collection of images. This collection features a wide variety of objects, including the specific animal species of interest. The richness and quality of this training data are crucial in ensuring that the model can accurately recognize animals in real-world settings. The training data is labeled with bounding boxes that are meticulously drawn around the targeted objects in each image, along with the corresponding class labels. This labeled information is utilized to teach the YOLOv5 model to recognize the distinct visual characteristics of different animal species.

• **Management of Video Frames:** The system captures live video frames from a camera (in this case, the built-in camera of the laptop). Each video frame is processed as an individual image and sent to the YOLOv5 model for analysis. Typically, the video frames are in RGB color format. The YOLOv5 model expects input images to be of a specific dimension (for example, 640x640 pixels). The cv2 library facilitates the acquisition of video frames and delivers them to the model. The model examines each frame separately and recognizes various objects.

b. Object Detection using YOLOv5:

The process for identifying animals relies on the YOLOv5 deep learning model:

- **Loading the YOLOv5 Model:** The YOLOv5 model is obtained using the torch. hub. load function from the ultralytics/yolov5 repository. This function retrieves the pre-trained model weights (specifically, 'yolov5s') and stores them in memory. The 's' in 'yolov5s' signifies that the model is small, which strikes a good balance between processing speed and precision.
- **Confidence Threshold:** The YOLOv5 model assigns a confidence score to each object it detects, indicating the level of certainty that the object belongs to a certain category. In this project, a confidence threshold of 0. 1 (10%) is implemented with model. conf set to 0. 1. This means that any detection with a score of 0. 1 or higher is considered valid. Lowering the confidence threshold increases the detector's sensitivity, allowing it to detect less visible or partially obscured animals. However, this also elevates the chances of false positives, which are instances where the model identifies something that isn't an animal.
- **•Detection Process:** On every video frame, the model(frame) method is invoked. The method conducts the forward pass of the YOLOv5 model on the frame, passing it through the model to get a list of detected objects. Every detected object is indicated by a bounding box (the rectangle's coordinates around the object), a class label (object type detected, e.g., "tiger," "elephant"), and a confidence score. The output of the model is in a format that includes the coordinates of the bounding box, the class label, and the confidence score for each detected object.

c. Animal Filtering

After the YOLOv5 model detects objects in an image, it filters the results to focus exclusively on the specified animals.

• filter_animals Function: The purpose of the filter_animals function is to extract the relevant animal detections from the initial output of YOLOv5. This function takes in the raw detection results along with a list of animal classes to be targeted, as specified in the configuration settings.

• Class Label Matching: This function goes through each detected object to obtain its class label. It then checks if this label matches any of the target animal classes. If there is a match, the corresponding detection is considered a legitimate animal sighting.

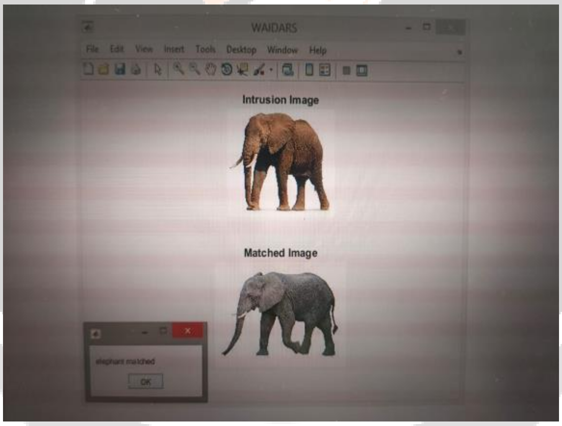


Fig 3: Animal detection

• Output: The function outputs a list containing the class labels of the identified animals. This list is restricted to include only those animals defined in the configuration settings, ensuring that the focus remains on the relevant species.

d. Alerting Mechanism

Once a target animal is identified, it notifies through the WhatsApp messaging system.

- **• WhatsApp Alert Function:** The send_whatsapp_alert function is responsible for dispatching the alert message. It uses the pywhatkit library to deliver the message to a specified phone number.
- **Configuration:** The phone number of the recipient is obtained from the config/config. yaml file. This setup enables straightforward customization of the alert recipient without needing to adjust the code.

- **Message Content:** The alert includes the name of the animal that has been detected (such as "? ? ? ? Wild Animal Detected: Tiger? ? ? ? "). This provides clear and direct information regarding the identified animal.
- **Message Sending:** The kit. send what msg_instantly function ensures that the message is sent right away. The wait_time parameter indicates the duration (in seconds) the function pauses before sending the message. This allows time for the WhatsApp application to open and for the message to be sent.

WhatsApp Alert Function:

The send_whatsapp_alert function is e.

- **System Configuration:**The system's characteristics, such as the specific animal species and the phone number for notifications, are established using a YAML file.
- **Configuration File:**The parameters for system configuration are stored in the config/config. yaml file. This file is accessed at the beginning of the program via the yaml. safe_load function.
- **List of Animals:** The configuration file contains a list of animal species that the system is designed to recognize. This feature allows the system to be conveniently adjusted for different settings and conservation needs.

•**Contact Number:** The recipient's phone number is included in the configuration file, allowing the system to send WhatsApp alerts. This ensures that notifications reach the correct person or group.

Output:

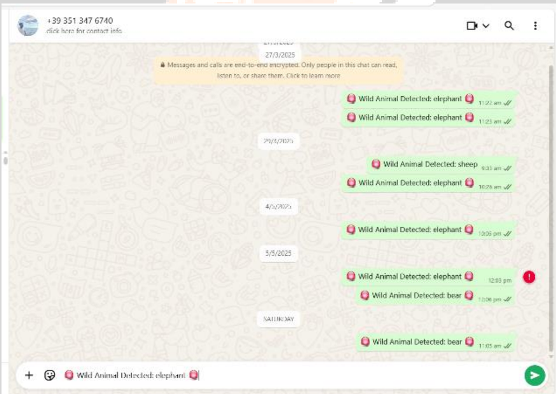


Fig 4: screen shot of alert message

4. RESULTS AND DISCUSSION

This part discusses how well the wildlife detection system works and what the results mean for reducing conflicts between humans and wildlife. It's important to mention that, because this project focuses on detecting objects, traditional classification measurements found in a classification report do not apply here. Instead, we utilize specific metrics and analyses that are suitable for evaluating the precision and success of detecting animals.

A. Animal Detection Performance

Evaluating the effectiveness of an object detection system requires metrics that assess both the ability to identify an animal's presence and the accuracy in pinpointing its location within the video frame. Here’s the approach we can take:

- **Precision and Recall:** These are fundamental metrics for evaluating object detection.
  - **Precision measures** The ratio of accurately recognized animals to the total number of detections made by the system. A high precision score indicates that there are few false positives(i.e.,instances where the system misidentifies an object as an animal when it is not).

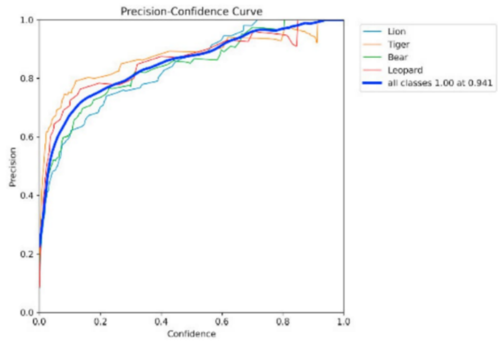


Fig 5: precision measures

- **Recall measures** the proportion of real animals depicted in the video that the system successfully identifies. A high recall indicates that the system is effectively recognizing most of the animals present.

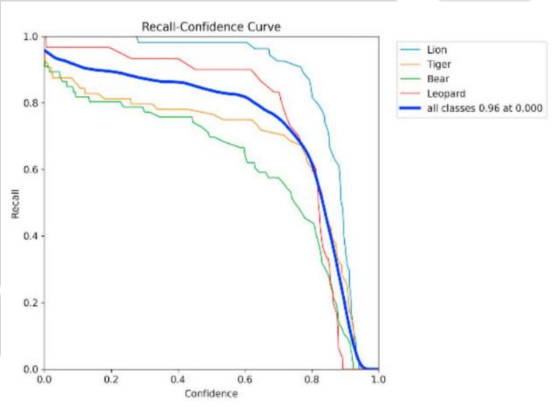


Fig 6: Recall measures

- **Average Precision (AP) and mean Average Precision (mAP):**
  - AP represents a measure that balances precision and recall for one specific animal category. It condenses the precision-recall curve into a single numeric value.
  - mAP is calculated as the average of the AP scores across all the animal categories being identified. In this study, when identifying several animal species (such as tiger, elephant, or deer), we will compute the AP for each species and then find their average to determine the mAP. mAP is widely recognized as a standard metric for evaluating object detection systems.
- **Intersection over Union (IoU):**

IoU represents the intersection between the actual bounding box (the real location of the animal in the picture) and the estimated bounding box (the rectangle the system creates around the spotted animal). A greater IoU indicates a more accurate localization of the animal. Typically, a threshold for IoU (such as 0. 5) is established to determine if a detection qualifies as a true positive.

- **Factors Affecting Performance:** The effectiveness of the system can be affected by several elements, including:
  - **Lighting conditions:**
    Insufficient light or shadows can impede the model's capacity to accurately identify animals.
  - **Weather conditions:** Poor visibility due to fog, rain, or snow can obscure animals and reduce detection effectiveness.

  - **Animal size and distance:** Identifying smaller or more distant animals might pose greater challenges.
  - **Occlusion:** Detection becomes more challenging when an animal is partially concealed by other objects.
  - **Image quality:** Low-resolution frames or unclear videos can decrease detection accuracy.

- **Evaluation in this project:** To thoroughly evaluate the effectiveness of this specific project, it is recommended to:

  - Capture video recordings from the desired setting (for example, near a forest).
  - Carefully annotate this video with accurate bounding boxes for the relevant animals.
  - Run the detection system on this annotated video.
  - Calculate the precision, recall, average precision, and mean average precision by comparing the ground truth labels with the system's results.
  - Examine the findings to pinpoint any shortcomings in the system and potential enhancements.

B. Discussion and Implications:

The results of the animal detection system are vital for preventing conflicts between humans and wildlife as well as aiding in wildlife conservation efforts.

•**Immediate Alert System**: A key benefit of this system is its capability to provide real-time alerts regarding animal sightings. This prompt notification allows for swift action, enabling authorities or local communities to take proactive measures to mitigate potential conflicts. For example, park rangers can be dispatched to deter animals, or local residents can be informed to implement safety measures.

•**Faster Reaction Time**: Unlike traditional methods such as manual patrols or periodic monitoring with camera traps, this system significantly reduces the time taken to respond after detecting animals. This improved response speed can be crucial in preventing dangerous encounters.

•**Ongoing Surveillance**: The system ensures constant observation of the specified area, guaranteeing that any animal presence is identified and reported immediately, regardless of the time or weather conditions (although effectiveness may vary).wildlife conflict mitigation and conservation efforts.

- **Conservation Information:** In addition to helping prevent conflicts, the system can provide valuable information that can be used for wildlife research and conservation efforts. Data regarding the presence, location, and occurrence of animals can help researchers gain insights into animal behaviors, habitat preferences, and population changes. This information can inform conservation strategies and help develop efficient methods to protect at-risk species.
- **System Information:** The system is affordable, utilizing low-cost hardware (a standard camera) and open-source software (YOLOv5). This makes it an ideal option for communities and organizations that have limited funds.
- **Scalable and Adaptable:** The system can be expanded to monitor larger areas by adding more cameras and can be customized to identify different species of animals by adjusting the configuration file. Its adaptability makes it suitable for a variety of uses.
- **Challenges and Future Developments:** It is important to acknowledge the challenges faced by the system. Detection can be affected by factors such as lighting conditions, weather changes, and visual obstructions. Future developments might focus on enhancing the system's resilience to these variables, potentially by employing more sophisticated image processing techniques or exploring the use of thermal imaging. Additionally, integrating the system with other data sources, like sound sensors or GPS tracking information, would provide a more comprehensive insight into animal behavior and movement.

5. CONCLUSION AND FUTURE WORK

This initiative has successfully demonstrated the potential for developing an automated system for detecting wildlife and sending alerts by leveraging computer vision techniques and instant messaging. The solution utilizes the capabilities of the YOLOv5 model for recognizing particular animal species in live video streams, offering a quick and effective means of identifying their presence in or near human communities and restricted zones. By integrating this detection feature with the widely accessible WhatsApp platform, the system delivers prompt notifications to relevant parties, enabling them to take preventive actions against human-wildlife conflicts and support conservation initiatives.

The system that has been created offers several significant advantages compared to traditional wildlife monitoring methods. Its ability to provide real-time notifications allows for immediate awareness of animal activity, greatly reducing the response time compared to manual patrols or standard camera checks. Quick responses are crucial for preventing dangerous encounters and minimizing damage to both human property and wildlife. The system ensures continuous monitoring, which allows for consistent detection and reporting of animal presence, regardless of the time or environmental factors. Furthermore, it is cost-effective, utilizing readily available hardware and open-source software, making it an ideal option for communities and organizations with limited resources. Its flexibility and ability to scale make it suitable for broader areas and for identifying a variety of animal species, enhancing its usefulness and practicality.

The project's achievement relies on the smooth combination of several essential technologies. The YOLOv5 model provides precise and swift object detection, and its use of a configuration file allows for easy adaptation to different settings and species. The WhatsApp notification system guarantees prompt and dependable alerts to the designated recipients. The system's modular design and use of shared components make deployment and upkeep rather straightforward. The initial rollout and testing have proven the system's ability to swiftly detect and notify about the presence of specific wildlife. This automated approach marks a significant advancement over traditional methods, delivering a more efficient, impactful, and cost-effective solution for monitoring wildlife and mitigating human-wildlife conflicts.

Despite the positive outcomes, there are several avenues for upcoming research to enhance the system's capabilities and address its limitations.

- **Enhanced Robustness:** It would be beneficial to pursue research aimed at increasing the system's robustness against harsh environmental conditions. This could involve exploring advanced image processing techniques to sustain performance despite changes in weather, lighting, and image clarity. Additionally, incorporating thermal cameras could improve functionality in low-light situations and enhance the ability to detect animals that are difficult to see visually.
- **Better Detection Precision:** Further optimizing the YOLOv5 model, for example, by fine-tuning it with a larger and more varied dataset specific to the environment of interest, can facilitate greater detection accuracy. This may entail employing advanced training strategies such as data augmentation and transfer learning to enable the model to adapt more effectively to different scenarios.
- **Compatibility with Other Sensors:** Integrating the system with additional sensor technologies might provide deeper insights into animal movement and behavior. For example, incorporating acoustic sensors could facilitate the detection of elusive animals, while GPS tracking information could offer valuable data regarding their location and movement patterns.
- Cloud-Based Processing: Transitioning to a cloud-based system could improve scalability and allow for better integration of sophisticated analytics. Additionally, cloud processing would facilitate the development of a unified monitoring system accessible to multiple users, providing a comprehensive overview of wildlife activity in a given region.
- **Smart Alert Management:** Implementing more sophisticated alert management strategies could boost system efficiency. This might involve designing algorithms to reduce false alarms, rank alerts based on threat levels, and provide detailed information about the detected animal, such as its size, movement direction, and behavior.
- **Drone Technology Integration:** Exploring the use of drones equipped with cameras and onboard processing could present a more efficient and adaptable method for overseeing extensive and remote areas. Drones could be utilized for aerial surveys, tracking animal migration, and supplying live video feeds to a centralized monitoring station.
- **Long-term Deployment and Assessment:** Implement the system in a natural setting (for instance, close to a village or along a forest edge) for an extended period. Collect data on its operational performance, including detection and false positive rates, as well as the alert system's ability to prompt appropriate responses. Gather input from stakeholders, such as local residents and forest rangers, about the system's functionality and overall value.

By focusing on enhancing these aspects of upcoming projects, the established system can become even better and more advanced, leading to a system that's both more effective and dependable for monitoring wildlife and preventing conflicts between humans and animals. The ultimate goal is to promote harmonious living between people and wildlife, protect vulnerable species, and ensure the safety and welfare of both humans and animals.

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  - This is the original paper introducing the YOLO (You Only Look Once) object detection framework. It's a foundational paper for understanding the technology used in your project.

- **Redmon, J., & Farhadi, A. (2018). Yolov3: An Incremental Improvement. *arXiv preprint arXiv:1804.02767*.**

  - This paper describes YOLOv3, an improved version of the original YOLO. While your project uses YOLOv5, understanding the evolution of the YOLO architecture is helpful.

- **Jocher, G., St রাতে, A., Chaurasia, J., & Kira, Z. (2020). yolov5. *GitHub repository*, https://github.com/ultralytics/yolov5. Accessed [Date of Access].**

  - This is a link to the YOLOv5 GitHub repository. It should be cited as the specific version of the software used. Replace "[Date of Access]" with the date you last accessed the repository.

- **Thorn, J. P., Rowcliffe, J. M., Cowlishaw, G., & Carbone, L. (2009). Evaluating the performance of camera traps as a tool for wildlife survey. *Journal of Applied Ecology*, *46*(3), 681-698.**

  - This paper provides a good overview of the use of camera traps in wildlife surveys, a traditional method that your project aims to improve upon. It gives context for the problem you are addressing.

- **Dickman, A. J. (2010). Complexities of conflict: the importance of considering social factors for effectively managing human–wildlife conflict. *Oryx*, *44*(03), 369-379.**

  - This paper discusses the complexities of human-wildlife conflict, highlighting the importance of considering social factors in developing mitigation strategies. It provides context for the real-world problem.

- **WWF. (Year). *Living Planet Report - 2024*. Gland, Switzerland: WWF.**

  - Cite the most recent WWF Living Planet Report. This report provides up-to-date information on the state of the planet's biodiversity and the challenges of human-wildlife conflict. Replace "Year" with the year of the report.

- **Uriot, V.J., Kellenberger, B., Begeot, S., Nguyen, A., Verdon, F., Joly, A., & Chen, C. (2021). Toward a global benchmark to assess animal detection in camera trap images. *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 278-288.**

  - This paper discusses benchmarks for animal detection in camera trap images, which is relevant to the evaluation of your system's performance.