

Eco-Watch Guardian AI-Enhanced Drone Patrols against Poaching

Submitted in partial fulfillment of the
requirements for the award of

Bachelor of Technology Degree in Information Technology

By

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DEPARTMENT OF INFORMATION TECHNOLOGY

SCHOOL OF COMPUTING

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Category-1 University by UGC

**Accredited with Grade "A++" by NAAC | 12B Status by UGC |
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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the Bonafide work of **Abhisheik.R (40120004)**, **Deepak.S (40120025)**, and **Naren.D (40120062)** who carried the project entitled "**Eco-Watch Guardian AI-Enhanced Drone Patrols against Poaching**" under my supervision from January 2024 to April 2024.

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ABSTRACT

The escalating threat of poaching and its devastating impact on wildlife populations have prompted conservationists to seek innovative and technologically advanced solutions. In recent years, the integration of unmanned aerial vehicles (UAVs), commonly known as drones, has emerged as a promising tool for anti-poaching and wildlife surveillance efforts. This paper presents an abstract overview of the implementation and effectiveness of drone patrolling in combating poaching and safeguarding wildlife.

Drones can efficiently cover large and inaccessible terrains, providing real-time surveillance to identify potential threats and monitor wildlife populations. Equipped with high-resolution cameras, thermal imaging, and advanced sensors, drones can detect poachers even under the cover of darkness or dense foliage, enabling timely intervention by law enforcement authorities.

Moreover, the incorporation of artificial intelligence and machine learning algorithms enhances the drone's capability to identify and differentiate between poachers and legitimate visitors or researchers, the data collected by drones can be analyzed to gain valuable insights into animal behavior, migration patterns, and habitat conditions, aiding in more informed conservation strategies. This paper highlights successful case studies from various regions where drone patrolling has significantly reduced poaching incidents and contributed to wildlife preservation. It also discusses ongoing research and potential future developments in drone technology to enhance anti-poaching efforts further.

In conclusion, the implementation of drone patrolling for anti-poaching and wildlife protection represents a transformative step in conservation practices. As technology continues to advance, integrating drones with other technologies like satellite monitoring and ground-based patrols can create a holistic and formidable defense against poaching, securing the rich biodiversity of our planet for generations to come.

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CHAPTER-1

INTRODUCTION

1.1 INTRODUCTION

The integration of unmanned aerial vehicles (UAVs), also called drones, have shown promise as a tool for anti-poaching and wildlife surveillance operations. An overview of the use of drone surveillance in preventing poaching and protecting animals is provided here. Large, inaccessible territory may be easily covered by drones, which can also provide real-time surveillance to spot potential dangers and keep an eye on wildlife populations. "Drones" can be categorized in numerous ways, such as according to their intended use, such as drones for photography.

Drones for surveillance, aerial mapping, and other uses. However, based on aerial platforms, it is possible to classify "drones" in the best way possible. Many fly at scaled speeds that are competitive with manned aircraft and are propelled by tiny gas engines, some even turbines. Due to the complexity of their control systems, multi-rotor UAVs differ from helicopters in that a computer is needed to manage control input. There are only propellers instead of a rudder or an aileron, unlike in planes. Drones can identify poachers even when they are hidden by night or thick vegetation because to their high resolution cameras, thermal imaging, and sophisticated sensors, allowing law enforcement to act quickly. An important development in conservation methods is the use of drone surveillance for anti-poaching and wildlife preservation.

There is simply no way to manually change the speed of the rotors, which is the only method to modulate modulator flight. They can essentially pilot themselves as a result of this fly-by-wire technology, especially when fitted with GPS, optical flow, and other guidance systems. Drones can be combined with other technologies, including as satellite monitoring and ground-based patrols, to build a comprehensive and powerful defense against poaching, protecting the wealthy.

Poaching presents a major danger to many species across the globe, driving several to the edge of destruction. Traditional conservation efforts have encountered difficulty tracking down broad and isolated regions where poaching typically occurs. Algorithms

based on machine learning allow the system to discriminate between people, cars, and animals, lowering false alarms and enhancing the accuracy of danger detection. Drones cover broad regions fast, decreasing the time necessary for manned patrols and boosting the overall efficiency of conservation activities. The abundance of data acquired by the drones helps decision-making based on evidence, supporting conservationists in understanding and managing concerns about the environment.

While drone patrols have showed efficacy in curtailing poaching, problems including as legislative applications, privacy issues, and the need for coordination between governments, conservation groups, and local populations persist. Future developments in drone technology, like greater travel periods, higher battery economy, and upgraded AI algorithms, offer promise for even more effective anti-poaching tactics. The delicate balance of ecosystems is increasingly under threat from forces such as worldwide warming, forest loss, and trafficking.

1.2 PROBLEM STATEMENT

"Endangered species and their ecosystems are in grave risk due to the ongoing menace of wildlife poaching. Traditional anti-poaching techniques frequently fall short of offering prompt and efficient protection because they are constrained by human surveillance capabilities and geographic restrictions. Due to this shortcoming, an inventive solution that strengthens animal conservation efforts by utilizing drone and artificial intelligence (AI) is urgently needed. Designing, creating, and putting into use an AI drone system that can independently identify and react to poaching activities in real-time, protecting sensitive wildlife populations and maintaining the integrity of protected areas, is the problem.

This problem statement concisely summarizes the issue, its importance, and the particular goal of your AI drone project, which is to use cutting-edge technology to stop wildlife poaching. Due to the complexity of their control systems, multi-rotor UAVs vary from helicopters in that a computer is required to handle control input. Cybercrime is also a worry because drones are susceptible to hacking and data exploitation.

1.3 AIM AND SCOPE

1.3.1 AIM

By effectively identifying, discouraging, and limiting unlawful poaching operations, an AI drone anti-poaching project aims to save wildlife and natural environments. The main goals are as follows:

- i. **Enhancing Wildlife Protection:** Using AI-enabled drones as a pro-active and trustworthy surveillance tool to protect fragile and endangered animals from the hazards of poaching and habitat degradation.
- ii. **Real-time Detection:** To create AI systems and drone capabilities that, even in difficult environmental conditions, can quickly and precisely identify poachers and their actions. Identifying and finding items of interest in real-time video sequences with quick inference and a minimal level of accuracy is a computer vision task.
- iii. **Swift Intervention:** In order to minimize damage to wildlife and improve the likelihood of catching poachers, it is necessary to enable fast response mechanisms, such as notifying law enforcement or park rangers, when poaching occurrences are discovered.

The ultimate goal is to encourage moral and sustainable conservation practices, dramatically lessen the negative effects of poaching on wildlife populations and ecosystems, and contribute to the long-term preservation of our planet's biodiversity.

1.3.2 SCOPE

The project's scope is broad and may include a variety of elements, tools, and applications for AI drone anti-poaching. An exhaustive scope of such a project is shown below:

- i. **Technology Development:** Design and develop AI algorithms that can identify wildlife, poachers, and suspicious activity from drone-captured imagery. For analysis of drone imagery as it is being recorded, real-time image processing capabilities are essential.

- ii. **Drone Technology:** Considerations including durability, payload capacity, and environmental adaptability should be taken into account when choosing or developing drones that are ideal for anti-poaching activities. Map and analyze changes in wildlife habitat, poaching hotspots, and patrol routes using GIS capabilities.
- iii. **User Interface and Visualization:** Create intuitive user interfaces so that operators can keep an eye on drone activities and access real-time data. Create comprehensible data visualizations using dashboards, graphs, and maps.

The goal of an ambitious AI drone anti-poaching project is to use cutting-edge technology to tackle a serious worldwide problem. To build a comprehensive strategy for wildlife conservation, it integrates technology innovation, environmental monitoring, law enforcement, data analysis, collaboration, and public involvement.

1.4 OBJECTIVE

It's crucial to be specific and focused on the aims of wildlife preservation and law enforcement when developing objectives for an anti-poaching project that makes use of AI and drones. A project to develop AI drones that prevent poaching has the following precise goals:

- i. **Poacher Detection:** Develop AI detection tools and drone capabilities to spot people poaching in protected wildlife regions. Use the project's findings to educate the public about the serious problem of poaching and its effects on ecosystems and wildlife.
- ii. **Real-time Monitoring:** Using drones, make it possible to monitor protected zones in real time and ensure quick response to suspicious activity. Drones can quickly fly over an area, identify dangers, and deliver aerial photos and real-time video.
- iii. **Rapid Response:** Establish a system that, when poaching activity is noticed, sends out automatic alerts to law enforcement or park rangers, enabling prompt intervention.

- iv. **Data Collection:** Use drones to gather information on poaching occurrences for evidence, including timestamps, locations, and suspected offenders.
- v. **Wildlife Protection:** Assess how the project would affect the amount of wildlife deaths and habitat devastation brought on by poaching.

1.5 APPLICATIONS

There many purposes of the applications for the project are to be used on:

- i. **Research Platform:** University researchers may test and assess novel theories using drones in a variety of domains, including robotics, real-time systems, navigation, and flight control theory.
- ii. **Investigating Purpose:** Drones can enter spaces that humans cannot, such as caves, holes, and tunnels, because to their small size and light weight.
- iii. **Shipping and delivery:** Major businesses support drone delivery. Drones may eliminate a lot of unwanted traffic on the ground and save a lot of labor. Additionally, they can be used to transport small goods, food, letters, medicines, beverages, and other items across shorter distances.
- iv. **Geographic mapping:** Drones, which are accessible to both amateurs and experts, can collect very high-resolution data and download imagery in inaccessible places like coastlines, mountaintops, and islands. Additionally, they are employed in apps that leverage crowd-sourced mapping to produce 3D maps.
- v. **Search and rescue:** Particularly in hostile environments or difficult terrains, drones can locate missing people and unlucky casualties. In addition to finding victims.

1.6 CONCLUSION

In conclusion, the nexus of AI and drone technology promises a potent and promising future in the ongoing struggle to safeguard the priceless species on our world. Drones have the ability to disrupt businesses and find innovative solutions to difficult problems as technology and AI develop.

CHAPTER-2

LITERATURE SURVEY

On-board energy, usually derived from fuel or electrical sources, frequently imposes restrictions on operation. This is especially true for long-duration missions like surveillance or reconnaissance. Exploring clean and renewable energy sources is therefore becoming more and more important in the aviation industry. Poachers still put endangered animals in peril and upset delicate ecosystems because of the illegal trade in animal parts and habitat damage. Innovative solutions that are as sophisticated as those attempting to exploit our planet's natural resources are required to address this dilemma.

The use of AI and drones in anti-poaching campaigns is more than just a technological innovation; it is a demonstration of our dedication to protecting biodiversity and the future of our planet's most vulnerable citizens. Due to the high heights at which aerial vehicles fly, solar energy is one naturally occurring resource that is plentiful and can be used. Due to advancements in aerospace and astronautics technology over the past ten years, interest in unmanned aerial vehicles (UAVs) has increased. Applications for UAVs are growing as sensors, motors, instruments become more precise, lightweight, and compact.

2.1 INFERENCES FROM LITERATURE SURVEY

[i] A vision-based unmanned aerial vehicle (UAV) pursuing system is proposed by the work of K. Kim, J. Kim, H. -G. Lee, J. Choi, J. Fan, and J. Joung and can be integrated into a pursuer UAV (pUAV) to defend against attacks by an evader UAV (eUAV). The two components of the proposed UAV chasing system are UAV tracking and control signal generating. The proposed UAV tracking algorithm can increase tracking performance of pUAV within an affordable computational complexity by combining a deep learning-based object detector, you only look once version three (YOLOv3), and existing object trackers. To reduce complexity, the object detector can be combined with the object tracker, which localizes the objects or provides the complete region occupied by the region at every time instant. [1].

[ii] In their research, P. Zhu, T. Peng, D. Du, H. Yu, L. Zhang, and Q. Hu suggested a large-scale video-based animal counting dataset for agriculture and wildlife protection called Animal Drone. Artificial intelligence (AI) is rapidly expanding since it has already been applied in a wide range of sectors, including the manufacturing and automotive industries. It's also intriguing to observe how AI combines with conservation of wildlife and agriculture. The dataset is divided into two parts: Part-A, which was obtained from on-site drone footage, and Part-B, which was obtained from online sources. Both parts provide rich annotations of more than 4 million items in 53,644 frames and related attributes for density, altitude, and view.

Despite significant advancements over the past few years, counting animals with drones is still difficult because of a variety of issues, including motion blur, scale fluctuation, a lack of positive sample size, and small items. Publicly accessible large-scale benchmarks and datasets are currently lacking for the development of drone-based animal counting systems. Despite the fact that there are numerous animal counting datasets for bats [1], penguins [2], and elephants [3], their data volumes, animal species, and scenarios they cover are still constrained. The problem of reciprocal occlusion between persons in a large density group in flat view observation can be avoided by drones' precise view. Drones are therefore ideal for counting animals. Over 4 million objects are annotated in 53,644 frames across a variety of situations in Animal Drone. The dataset for animals from drones contains 10 different species.

[iii] The work of H. Kim, J. Ben-Othman, L. Mokdad, J. Son, and C. Li explains how the AI-VEmoBAR, AI-VEmoFLOW, and AI-VEmoMAP function as well as applicable scenarios. The development of SIEM system architectures [1,2], the identification of threat sources and mechanisms for their detection in distributed systems [3-5], the blocking of malicious traffic from IoT devices, and the investigation of intellectual data processing from various sources using event classification methods [6] have all received significant attention in recent years. The extraction of data that is relevant for access control [7], the study of user behavior, and circumstances involving computer security specifically in various surroundings are the focus of other research directions.

2.2 MARKET POTENTIAL FOR DRONE MANUFACTURING

It is expected that India's \$830 million UAV market will expand at a compound annual growth rate (CAGR) of 14.5 percent between 2021 and 2026. Considering that, according to a research, the global market for UAVS is currently worth \$21.47 billion. By the end of 2021, the Indian UAV industry might reach \$900 million. (ORF). The government projects that over the next three years, the drone manufacturing industry will spend more than Rs.5000 crore and add 10,000 new direct jobs. By FY24, it forecasts an increase in income for the drone manufacturing industry from its current level of Rs.60 crore to Rs.900 crore.

The realization of multiple use cases across numerous industries has led to an exponential rise in demand for the sector serving local and international markets. Aside from necessities for research, development, and military and security, government authorization is now required for the import of drones. In order for the local drone industry to grow more swiftly than its international competitors, the government will be crucial. The government is on the right track with its indigenization programs, which it initiated through a series of legislative amendments and financial support.

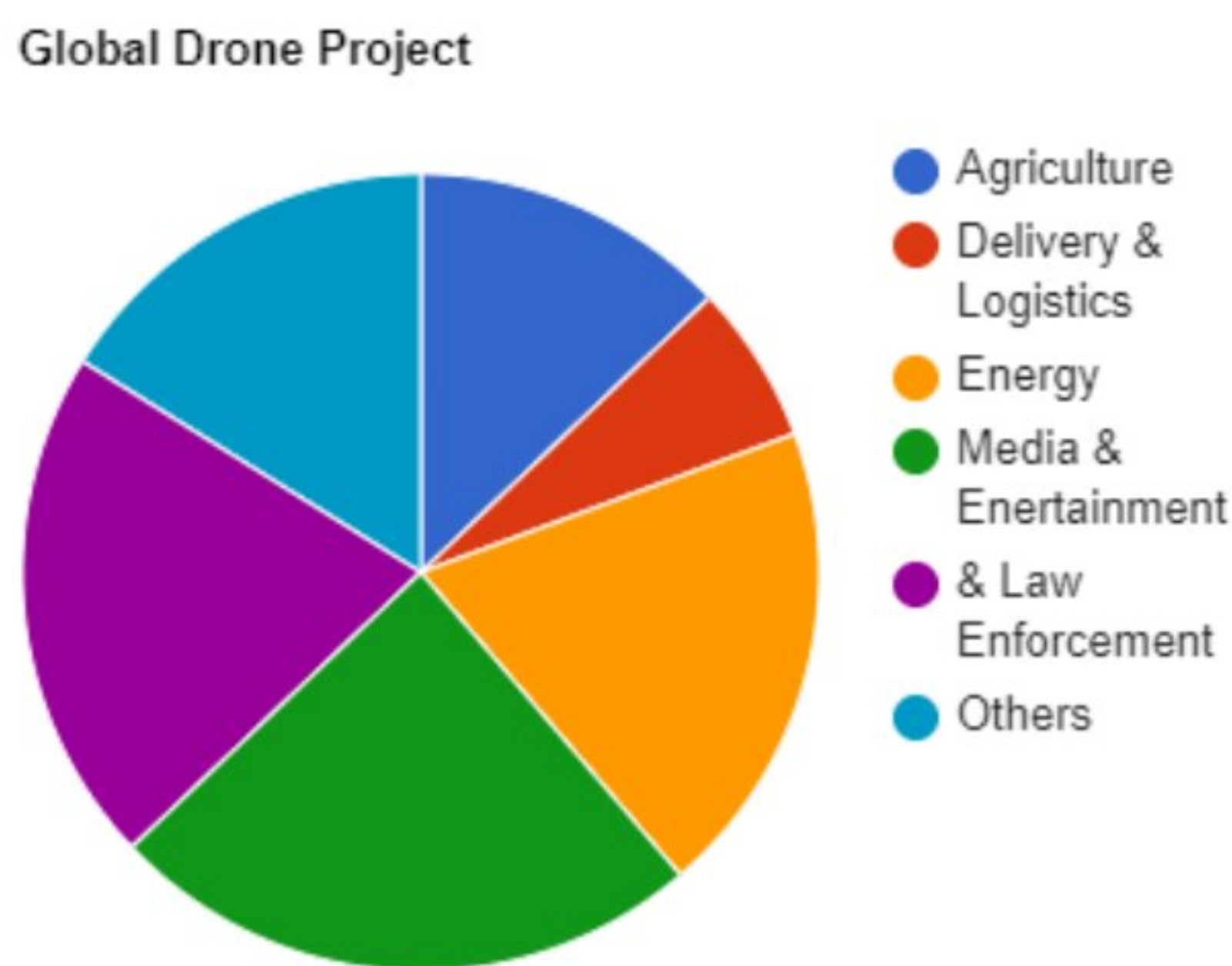


Figure 2.1 Global Drone Project

Drone component imports will still be allowed. This was done when the nation's drone registration and usage laws were relaxed. In addition, the nation's drone production has been encouraged by the launch of the Rs.120 crore Production Linked Incentive (PLI) program. In FY21, the total income generated by all domestic drone manufacturers was almost exactly twice as much.

2.3 EXISTING SYSTEM AND PROPOSED SYSTEM

- **Existing System**

- i. Smart Parks uses AI drones to safeguard animals in national parks and reserves in collaboration with a number of conservation groups. In order to recognize potential dangers and poachers, their method uses machine learning.
- ii. To take pictures and films of wildlife and possible poachers, motion-activated camera traps are positioned strategically in wildlife areas. They can be used to monitor wildlife numbers and acquire evidence.
- iii. Park rangers' traditional ground patrols continue to be a key part of the fight against poaching. Rangers keep an eye out for evidence of illicit activity, including as poaching, logging, and habitat destruction, in protected areas.
- iv. The unique system, built for extensive gathering and interpreting of data, meets the rising demand for updated data to support conservation initiatives, disaster response, and efficient use of resources.
- v. Robust communication technologies, such as long-range radio transmitters or satellite connections, are installed aboard the drone to provide dependable contact even in distant locations. This makes it possible for the drone, control center, and other anti-poaching stakeholders to communicate seamlessly with one another.
- vi. The drone may navigate on its own by either automatically adhering to pre-established routes or changing its course dynamically in response to mission goals and real-time data.

- **Proposed System**

- i. To improve wildlife protection, a suggested anti-poaching system should make use of current technologies and best practices.
- ii. The suggested Eco-Watch Guardian AI-Enhanced Drone Patrols provide a groundbreaking way to tackle the continuous menace of illegally harvesting wildlife.
- iii. By blending state-of-the-art artificial intelligence with modern drone technology, this system is aimed to offer an anticipatory, efficient, and physically resilient solution to the complex issues connected with safeguarding endangered species and their ecosystems.
- iv. The rising issues faced by environmental changes, habitat degradation, and natural catastrophes, a suggested system employing drone technology promises to modernize monitor the environment.
- v. A thorough anti-poaching strategy must include technology, community involvement, legal backing, and a dedication to long-term sustainability. A system like this can efficiently dissuade poachers while considerably enhancing the preservation of species and their habitats.
- vi. Consistently update and modify the system in light of new technological advancements and lessons learnt.
- vii. Assess the system's performance using data analysis and input from field teams.

CHAPTER-3

METHODOLOGY AND TECHNOLOGIES

In the context of an AI drone anti-poaching project, methodology refers to the methodical approach and set of steps used to develop, carry out, and assess the project's goals. It includes all of the methods, procedures, and methods used in the development, application, and evaluation of AI drones for anti-poaching operations. The technique for such a project might look like this, broken down:

- i. **Problem Identification:** Start by describing the wildlife poaching issue in the target area in detail. Recognize the particular difficulties, the species of wildlife that are endangered, and the tactics used by poachers.
- ii. **Stakeholder Engagement:** Engage with the appropriate parties, such as local residents, conservation groups, wildlife authorities, and drone specialists. To help with project planning, gather information and viewpoints.
- iii. **Objective Setting:** Establish the project's aims, including the precise anti-poaching targets you want to hit using AI drones. These goals ought to be in line with the existing issue.
- iv. **Technology Selection:** Depending on the needs of the project, select the right drone hardware and software technologies. Make sure the AI algorithms you use are appropriate for tracking wildlife and detecting poachers.
- v. **Data Collection Plan:** Create a strategy for data collection, deciding on the drones' sensors to be employed (such as cameras or thermal imaging). Establish the drone flights' frequency and area of operation.
- vi. **Drone Deployment:** Create a drone deployment plan, taking into account things like flight paths, altitudes, and the incorporation of real-time data transmission. Create a thorough aerial surveillance strategy that specifies the goals, routes, and catchment areas for drone operations. Think about the protected area's particular requirements.
- vii. **Monitoring and Evaluation:** Continuously monitor drone operations and anti-poaching efforts. Evaluate the effectiveness of AI algorithms in poacher detection and wildlife protection.

- viii. **Legal and Ethical Considerations:** Make sure that drone operations and the preservation of wildlife are conducted in accordance with all applicable national, international, and aviation rules.
- ix. **Sustainability Plan:** Create a sustainability strategy to guarantee the AI drone anti-poaching system's continuing use after the project's initial stage. To guarantee the continuation of the project, obtain multiyear financing pledges from philanthropists, philanthropic organizations, or governmental entities.
- x. **Community Involvement:** Engage the neighborhood to get their help and cooperation in the fight against poaching. Create procedures for community reporting of shady activity.

A planned and methodical strategy is provided by the methodology to direct the AI drone anti-poaching project from conception to deployment and ongoing evaluation. It ensures that the project is carefully thought out, effectively carried out, and capable of accomplishing its conservation objectives.

3.1 DESIGN CONSTRAINTS AND DESIGN METHODOLOGY

When we first started designing and planning the project, we ran into problems with a scarcity of parts and the difficulty of obtaining them quickly enough for our project, such as the need for specialized motors and control systems to help lift the design. Additionally, the majority of the components were imported since they were unavailable in the local market, and a number of businesses declined to work on the design because they lacked the necessary authorization. The design was requested from PMU for the senior graduation project of a student, and all experiments will be conducted on the university's campus to develop the movement of the drone. Eventually, one company agreed to complete the design in shape only without creating any programming for the control system. We informed them of this and explained that all experiments would be conducted there. To raise the design without causing any overloading, however, and to make it easier to fly, we need pay attention to the weight of the design and concentrate on the motor's thrust strength. Establish mechanisms for knowledge transfer and capacity building to ensure that project expertise is passed on to new team members.

3.1.1 SUSTAINABILITY

Due to the possibility of slight vibration, we can encounter a sustainability issue. We picked a smaller, more efficient fan because of the thickness and angle of the fan's blades and to prevent this issue so that the motor movement during the thrust would be compatible.

3.1.2 SAFETY

One of the key components of our system is the safety of the parts, which keeps the motor from being overloaded and improves the effectiveness of the quadrotor rising and stabilizes the fan's movement. To better utilize resources and knowledge, fortify alliances with international organizations, governmental organizations, and conservationist groups.

3.1.3 ETHICAL

This project is almost identical to the earlier types of works. In order to improve the design in terms of safety, economy, and sustainability, we sought for some general principles.

3.2 FEASIBILITY STUDY

In the context of an AI drone anti-poaching project, a feasibility study is a thorough evaluation of the project's viability, applicability, and merit. It entails assessing many facets of the project to ascertain its likelihood of success and sustainability. A feasibility study for AI drone anti-poaching includes the following steps:

- i. **Technical Feasibility:** Evaluate the project's objectives and the availability of the necessary AI and drone technology. Analyse the abilities of AI systems for tracking wildlife and detecting poachers. Check to see if the essential drone hardware is available and able to complete the relevant tasks. Organize regular reporting and communication with stakeholders, donors, and the general public about the status and results of the project. Continuously monitor and evaluate the project's impact, adjusting strategies as needed to achieve conservation goals effectively. It will develop an exit strategy that outlines steps for project transition or closure if sustainability cannot be maintained.

- ii. **Economical Feasibility:** In order to determine the economic viability of developing and operating an AI drone system to combat poaching, it is necessary to weigh the costs, advantages, and prospective economic effects. Calculate the project's initial and continuing expenditures, including those associated with the purchase of drones, the creation of AI software, instruction, operational costs, and maintenance. Consider cost savings, a drop in poaching instances, and the advantages to conservation when calculating the possible return on investment (ROI). It offers insightful information on the monetary viability and prospective economic gains of such a conservation program.
- iii. **Legal and Regulatory Feasibility:** Examine the laws that apply to the project's target area's drone activities, data gathering, and animal protection. Make sure all aviation rules, laws protecting wildlife, and privacy rules are followed. An AI drone anti-poaching project must be evaluated for its legal viability, which includes determining whether it complies with all applicable laws, rules, and legal requirements. It guarantees that the project can be carried out within the restrictions set by the laws governing drone operations, wildlife protection, and data privacy.
- iv. **Operational Feasibility:** In the context of an AI drone anti-poaching project, operational feasibility measures how well the proposed system can be implemented and incorporated into the current environment. It entails assessing the viability of using AI-equipped drones in anti-poaching operations. The fleet of drones' access to resources for maintenance and support. Create upkeep plans and methods to keep the drones operating. The ability of the AI drone anti-poaching system to be actually implemented and successfully incorporated into the ongoing conservation and law enforcement operations is a crucial aspect of project planning.

3.3 ARCHITECTURE

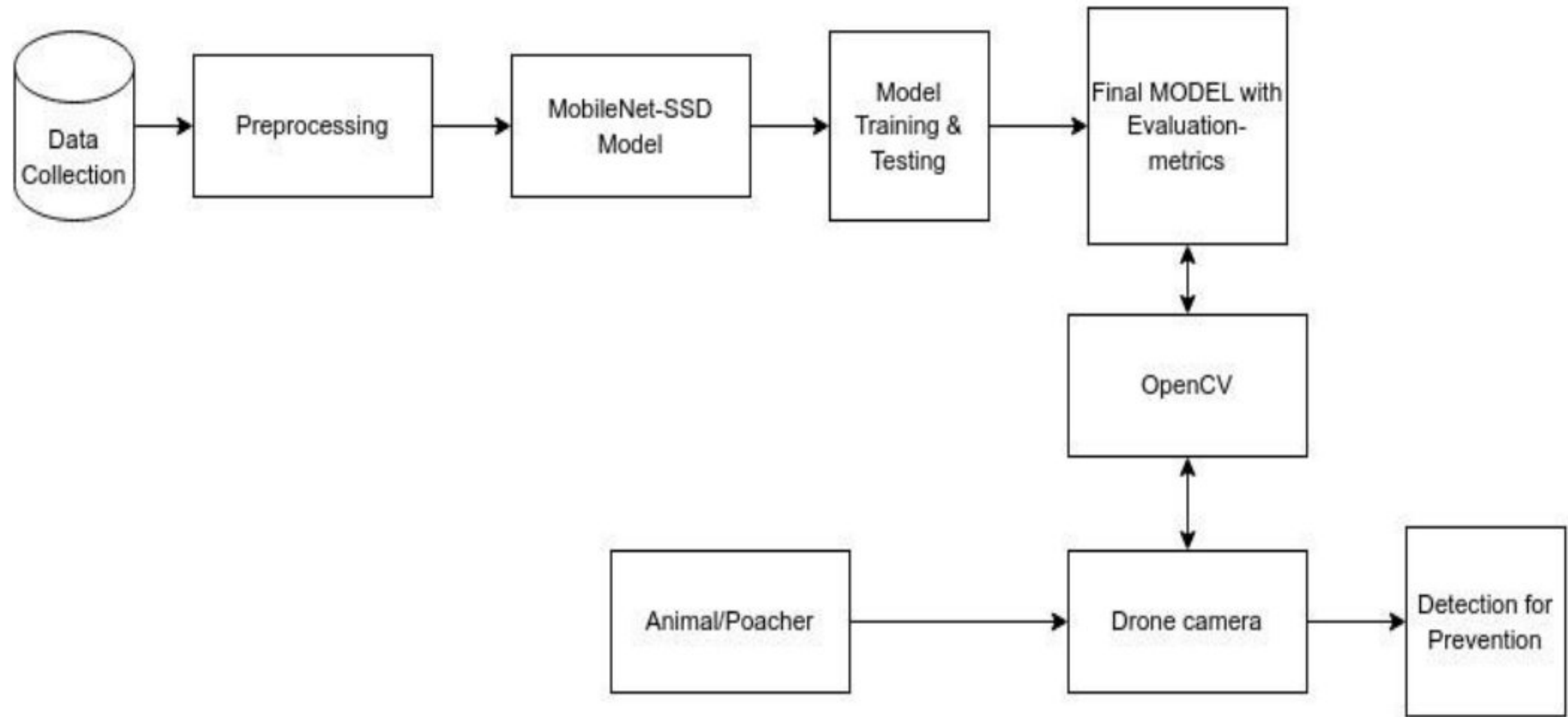


Figure 3.1 Model Architecture

The architecture proposed for animal poacher detection utilizing a TensorFlow model involves a multi-stage process that integrates advanced deep learning techniques. The first stage of the architecture comprises a comprehensive dataset collection, including images from various wildlife habitats and potential poaching scenarios.

3.3.1 DATA COLLECTION

The ability to get important information for analysis and decision-making depends on data collection, which is an essential component of its functioning. The following are some important details of the drone's data collection:

- i. **Video and Image Capturing:** The drone has high-definition cameras that can record both still and motion pictures. Real-time monitoring of animals and any poaching operations is done with the usage of this data.
- ii. **GPS and whereabouts Information:** The drone can precisely monitor its whereabouts thanks to integrated GPS technology. Mapping patrol routes, pinpointing poaching hotspots, and tracking animal migrations all depend on this data.
- iii. **Storage and Backup:** While flying missions, the plane's storage facility may be used to temporarily store data. Furthermore, data is safely stored up to guard against loss and allow for further analysis after transmission.

3.3.2 PREPROCESSING

Pre-processing is essential to guaranteeing that the data is correct, pertinent, and fit for further examination. The drone system may do the following crucial pre-processing steps:

- i. **Normalization:** Data is standardized and brought to a consistent scale via the use of normalization. When working with data from several sensors or sources that can have varied ranges or units of measurement, this is crucial. Normalization provides reliable comparison and analysis of the data.
- ii. **Data Fusion:** To provide a more complete image, data fusion merges information from many sensors or data sources. For instance, integrating GPS coordinates, ambient sensor readings, and thermal imaging data might improve the detection and monitoring of poaching operations.
- iii. **Data compression:** By compressing the gathered data while maintaining critical information, data compression methods may be used to lower storage and transmission overhead. When it comes to massive amounts of sensor data gathered during drone patrols, this is really helpful.

3.3.3 MOBILENET-SSD MODEL

A well-liked deep learning architecture for object identification tasks is the MobileNet-SSD (Single Shot Multibox Detector) model. It is used in aerial surveillance applications like the Eco-Watch Guardian AI-Enhanced Drone patrols against poaching. The drone system may be linked with the MobileNet-SSD concept in the following ways:

- i. **Object detection:** The MobileNet-SSD model's main job is to identify and categorize things in pictures or video frames that the drone's cameras have taken. This entails recognizing animals, possible poachers, cars, and other pertinent items within the drone's visual range.
- ii. **Real-Time Processing:** The MobileNet-SSD model can handle live video feeds from the drone since it is designed for real-time inference. This makes it possible to respond quickly to any dangers or irregularities found while on patrol.

- iii. **Alert Generation:** The MobileNet-SSD model has the ability to send notifications or alerts to operators or appropriate authorities when it detects items of interest, such as possible poachers or illicit activities. This makes it possible to respond quickly to stop poaching occurrences or save animals.
- iv. **Poacher Detection Model:** A MobileNet-SSD model specifically designed to identify poacher's concentrates on identifying people, cars, and questionable actions connected to poaching. It can recognize people going into restricted regions, illegal cars, and actions like carrying guns or creating traps.

3.3.4 MODEL TRAINING AND TESTING

To guarantee the efficacy and dependability of models in a drone system for tasks like object identification, navigation, and decision-making, a number of crucial procedures must be taken during training and testing. An outline of how model testing and training may be done in a drone is provided below:

- i. **Model Choice:** Select the proper deep learning or machine learning models according to the drone system's goals and duties. Convolutional neural networks (CNNs) are often used in drones for image processing tasks including object recognition, while recurrent neural networks (RNNs) are frequently utilized for navigation and sequence prediction in drones.
- ii. **Validation:** To assess the model's performance during training, put aside a subset of the data. Assess the model's efficacy using measures including accuracy, precision, recall, and F1 score.
- iii. **Training Procedure:** Use the pre-processed data to train the chosen models. This entails feeding the model with data, iteratively enhancing the model's performance, and optimizing the model's parameters via gradient descent and back propagation.
- iv. **Constant Monitoring and Updating:** Throughout drone operations, keep an eye on how deployed models are doing. Models may be updated and retrained with fresh data as required to handle new problems, enhance accuracy, and adjust to evolving situations.

3.3.5 FINAL MODEL WITH EVALUATION-METRICS

Several important steps must be taken to make sure that the end model with evaluation measures in a drone can do things like finding objects, navigating, and making decisions. Following are the steps you need to take to create and test the end model in a drone system:

- i. **Model Selection and Training:** The review measures that will help you judge how well the model did on the tasks that were given. For classification tasks, accuracy, precision, recall, F1 score, mean average precision (MAP), and area under the curve (AUC) are all common ways to measure performance.
- ii. **Continuous Monitoring and Improvement:** To keep an eye on how the launched model is doing during drone flights and collect feedback and data to keep improving the model. As needed, add new data and insights to the model and update it so that it can adapt to changing risks, business needs, and the environment.

3.3.6 DETECTION FOR PREVENTION

Detection for prevention in a drone system includes using advanced technologies and algorithms to identify possible risks or illegal actions early, allowing for quick involvement and prevention. Here's how detection for protection can be performed in a drone system:

- i. **Sensor Integration:** Equip the drone with a range of sensors such as high-resolution cameras, thermal image cameras, LiDAR (Light Detection and Ranging), GPS, and weather sensors. These devices provide complete data for research and discovery.
- ii. **Anomaly Detection:** Utilize anomaly detection techniques to find odd patterns or actions that differ from standard situations. This could include spotting illegal entry into limited places, odd wildlife behavior, or suspicious human activities.
- iii. **Integration with Command Center:** Establish contact and data sharing between the drone and a central command center or control room. Transmit real-time data, tips, and warnings to workers for instant review and decision-making.

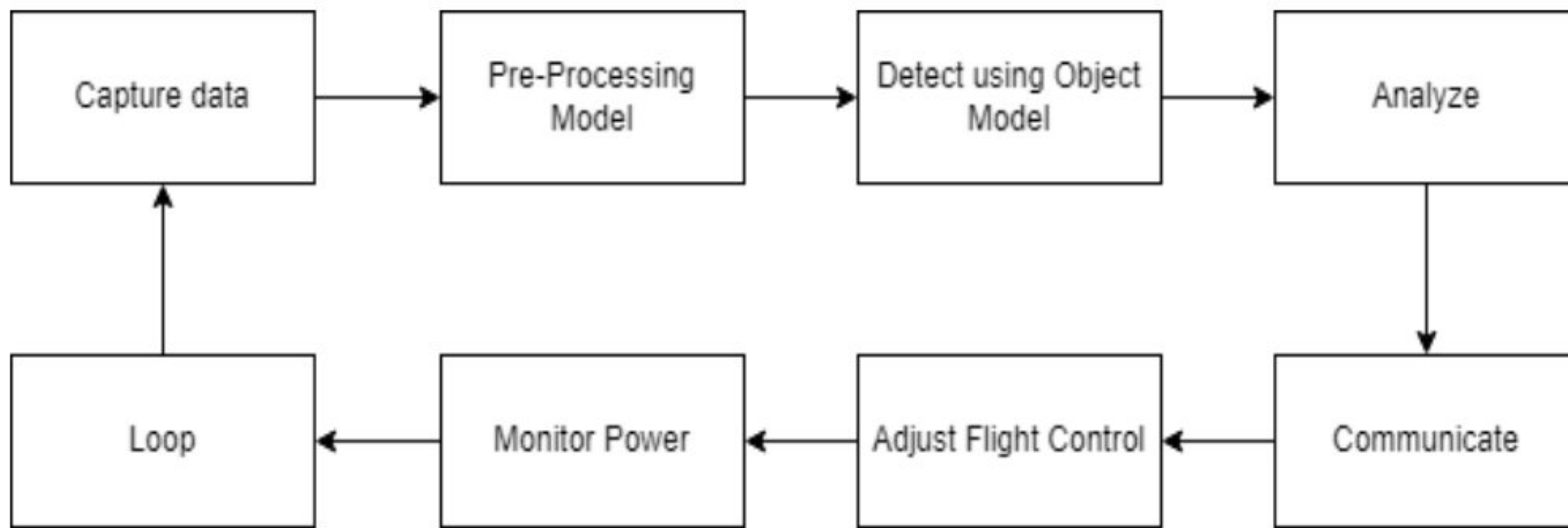


Figure 3.2 System Architecture

The system architecture for deploying drones in anti-poaching efforts requires a combination of hardware components, software systems, and communication networks to enable effective observation, detection, and action regarding poaching activities. The core of the architecture relies on a Convolutional Neural Network (CNN) implemented through Tensor Flow, a powerful open-source machine learning framework. The CNN is specifically designed to extract intricate features from wildlife images, allowing the model to discern potential threats and identify distinct patterns associated with poaching activities. The method of transfer learning is applied by using models that have been trained before, allowing the network to exploit information obtained from large-scale picture datasets.

The model's performance and simplify detection in real-time, the architecture incorporates a streamlined inference pipeline. This involves deploying the trained TensorFlow model on edge devices or cloud platforms, ensuring efficient processing of incoming data streams. The GCS is where operators watch and control the drone. It typically contains of a computer or console with software that gives real-time telemetry data, video feed from the drone's cameras, and interfaces for controlling flight parameters and mission planning. Securely flying, drones generally feature redundancy in crucial components such as flight control, power supply, and communication connectivity. They may also have safety features including fail-safe modes, automated return-to-home in case of signal loss, and collision avoidance systems.

3.4 SYSTEM REQUIREMENTS

Hardware Requirements

Flight Controller	: It likely includes a microcontroller or a dedicated flight control unit designed by DJI.
Camera	: The camera on the DJI Tello is a 5-megapixel camera capable of capturing 720p video.
Processor	: Intel Movidius Myriad 2 VPU (Vision Processing Unit).
Battery	: 3.8V 1100mAh LiPo battery.
Sensors	: Infrared sensors, downward-facing vision system (camera), and barometer for altitude hold.
Wi-Fi Module	: Wi-Fi module for communication with a mobile device for control and live video streaming.

Software Requirements

Flight Control Software	: ArduPilot
AI Algorithms	: TensorFlow Object Detection API
Machine Learning Framework	: TensorFlow, Darknet
Libraries Used	: OpenCV, NumPy, Matplotlib, sklearn, Pandas

3.5 DESCRIPTION OF SOFTWARE FOR IMPLEMENTATION OF THE PROPOSED MODEL/SYSTEM

To implement the model, execution of program is done through Jupyter Notebook. Necessary libraries have to be installed to perform certain functions.

DESCRIPTION OF PROGRAMMING LANGUAGES AND SOFTWARE

Python, a general-purpose high-level programming language, is widely used. The cutting-edge technology in the software business, including web development and machine learning applications, all employ the Python programming language. Python is often used to develop software for controlling drones and automating their operations. This includes writing scripts and algorithms for flight control, navigation, and mission planning. Python's readability and ease of use make it well-suited for developing complex drone control systems.

Jupyter Notebook, is a popularly used interactive, web-based computational platform for data science, education, and research. Users can create and share documents that include narrative prose, mathematics, live code, and visualizations. It is a priceless tool for collaboratively analyzing data, running experiments, and sharing reproducible research findings because users may run code cells one at a time, examine results, and record their thought processes.

TensorFlow, is an open-source machine learning framework created by Google that is strong and popular. TensorFlow, which is renowned for its adaptability and scalability, enables researchers and developers to create and use machine learning models in a variety of applications. TensorFlow is appropriate for projects of all complexity levels because it makes it simple for users to build neural networks, provides both high-level and low-level APIs, and enables distributed computation. TensorFlow continues to lead the field of machine learning thanks to its large and vibrant community, which fosters creativity and enables the creation of cutting-edge AI solutions.

DESCRIPTION OF LIBRARIES USED

OpenCV, OpenCV, short for "Open Source Computer Vision Library," is a comprehensive and widely-used open-source software library designed for computer vision and image processing tasks. It offers a rich set of tools, functions, and algorithms that allow researchers to effectively manipulate and manipulate images and videos. OpenCV supports various programming languages, including C++, Python, and Java, making it accessible for a wide range of applications.

NumPy, which stands for "Numerical Python," is the cornerstone library for numerical and scientific computing in Python. It offers support for creating, manipulating, and performing operations on arrays and matrices, making it a crucial tool for data analysis, machine learning, and scientific research. Its effective implementation in C and integration with Python allows for high-performance computation and seamless integration with other scientific libraries.

Matplotlib, is an indispensable tool for data analysis, scientific research, and data presentation since it is a flexible Python library for producing a wide range of static, animated, and interactive visualizations. Matplotlib enables users to create high-quality plots, graphs, and figures to effectively communicate complicated data and insights because to its vast range of chart types, customization options, and support for numerous output formats. The library also interfaces smoothly with other Python libraries and tools often used in data analysis and scientific computing, such as NumPy for numerical computations, Pandas for data manipulation, and Jupyter notebooks for interactive data exploration and visualization. Matplotlib gives you the flexibility and control necessary to build interesting and useful data visualizations in Python, whether you're making straightforward line charts or complex 3D representations.

Scikit-learn, is a well-known open-source machine learning package for Python that is frequently used. For numerous machine learning tasks, such as classification, regression, clustering, dimensionality reduction, and model selection, it offers an extensive and user-friendly toolkit. With its uniform API, Scikit-learn streamlines the machine learning workflow, making it simple to develop, train, and assess machine learning models. Its comprehensive collection of algorithms, preprocessing methods, and assessment measures makes it an invaluable tool for machine learning professionals and newcomers alike, encouraging the quick creation of prediction models and data-driven insights.

Pandas, a well-known open-source Python package for data analysis and manipulation is called Pandas. It offers strong data structures that facilitate effective data cleaning, transformation, and exploration, such as data frames and series. Pandas' data structures, such as Data Frames and Series, can be utilized to conveniently handle and analyze this data. For example, you may use Pandas to arrange and evaluate sensor data collected by drones for diverse applications like environmental monitoring or infrastructure inspection. Reading and writing data from diverse sources, addressing missing values, and carrying out aggregation and statistical calculations are all made easier by Pandas.

3.6 DESCRIPTION OF HARDWARE REQUIREMENTS

The Components which is employed for creating Quadcopter Drone:

Frame: If you need a frame for your drone, you have two options. You may either create it yourself or get it from an online retailer, but if you'd want some excellent options for premium frames, check out our post on the top drone frames. The project isn't that hard if you decide to do it yourself, but you will need some understanding of engineering and the materials you'll be using. For instance, you may use plastic, aluminum (anything light), or even wood planks. You will want a hardwood board that is around 2.5 cm thick if you choose to go with a wooden frame.

Motors: An octocopter needs eight motors to fly, but a regular quad only needs four. The recommendation is to use brushless motors since they are easier on batteries and should be purchased from a store unless you are an engineer who is well-versed in motor operation. You may also read our article on drone motors to get more knowledgeable about them. Electronic speed controllers, or ESCs, are another crucial component of your drone as they provide power to the motors. Once again, the quantity of them is determined by the number of arms your drone will have.

Propellers: Propellers are crucial components of drones that are responsible for generating thrust and enabling flight. They are rotating blades or fans that create lift by pushing air downward, following the principles of Newton's third law of motion (for every action, there is an equal and opposite reaction). Look for propellers that fit your drone's frame while you're looking for them. Focus on the materials: although wooden propellers are not available, make sure the ones you choose are a true fit. Connections 3.5 mm and 4.5 mm connections are required for the facility distribution board and the motors and ESCs, respectively, to be welded.

Batteries: Batteries are fundamental components of drones as they provide the necessary power for propulsion, control, and onboard systems. It's important to consider a battery's capacity and kind when buying batteries for your drone. Li-Po batteries are the most often used batteries for this purpose, and they vary in power. To have a deeper understanding of this topic, we highly recommend reading our article on drone batteries.

Battery Monitor: While this is usually not a basic item, it may be somewhat helpful in alerting you when the batteries are about to run out. This way, you don't have to worry about the drone running out of battery when it's over a pond. A battery monitor makes sure that your aerial vehicle won't run out of juice at the worst possible time.

Camera: You'll need a camera if you want to take aerial pictures and document the surroundings while operating your drone. The most basic cameras are those that can capture normal 4K footage, however there is a camera out there that will suit everyone's requirements. You could also need a camera gimbal for professional aerial photography and filmmaking.

3.6.1 VERTICAL MOTION

Drones use rotors for propulsion and control. A rotor as a lever, because they work just about an equivalent. Spinning blades push air down. Of course, all forces are available pairs, which means that because the rotor pushes down on the air, the air pushes abreast of the rotor. This is often the essential idea behind lift, which comes right down to controlling the upward and downward force. The faster the rotors spin, the greater the lift, and vice-versa. Now, a drone can do three things within the vertical plane: hover, climb or descend. To hover, the internet thrust of the four rotors pushing the drone up must be adequate to the gravity pulling it down. Easy. So what about moving up, which pilots call climbing? Just increase the thrust (speed) of the four rotors so that there's a non-zero upward force that's greater than the load. then, you'll decrease the thrust a touch bit—but there are now three forces on the drone: weight, thrust, and air drag. So, you'll still need for the thrusters to be greater than just a hover. Vertical motion in drones refers to the ability of drones to ascend (move upward) or descend (move downward) vertically. This capability is essential for various drone operations, including takeoff, landing, altitude control, and vertical maneuvers during flight. Vertical motion is typically controlled using the drone's propulsion system, which includes motors, propellers, and flight control algorithms.

3.6.2 TURNING (ROTATING)

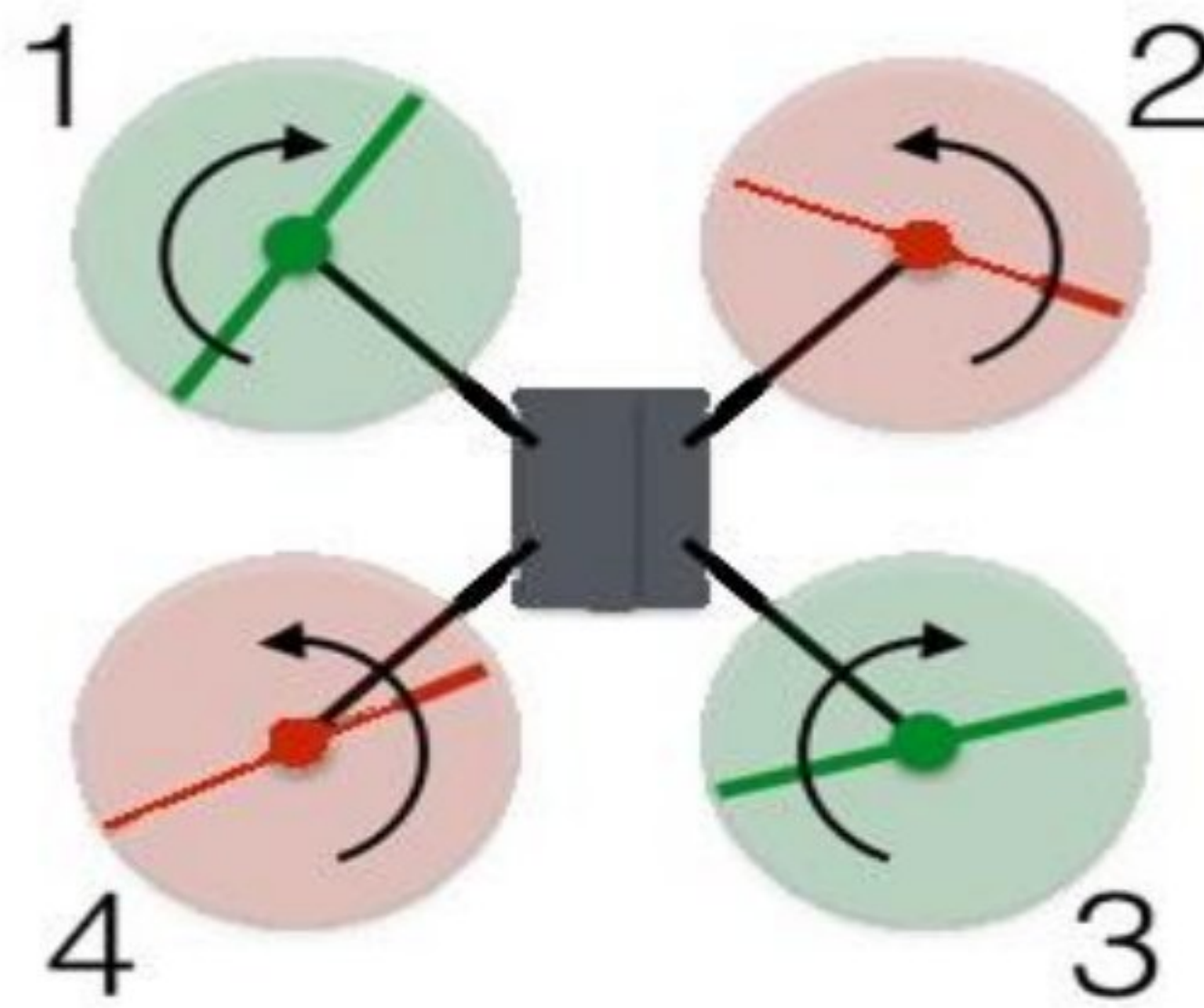


Figure 3.3 Actual Motor working

In the above Figure 3.3, the red rotors revolving in the opposite direction of the clock, the green rotors are rotating in the other direction. Each of the two sets of rotors is spinning in the opposing direction, which results in the total momentum being zero. The calculation of momentum involves multiplying the angular velocity by the instant of inertia. Momentum may be calculated in a manner that is quite similar to linear momentum. In the event that there is no torque on the system, which in this instance is the drone, then the total momentum must stay constant, which is 0 in this particular instance. Just to create things simpler to know, I will be able to explain the red counterclockwise rotors have a positive momentum and consequently the green clockwise rotors have negative momentum. I'll give each rotor a value of +2, +2, -2, -2, which adds up to zero (I left out the units).

CHAPTER-4

RESULT AND DISCUSSION

4.1 RESULTS

The results of our custom-built dataset's object detection, which properly identified and localized items, are displayed below.

This is the prediction of the animal labeled “Tiger”:

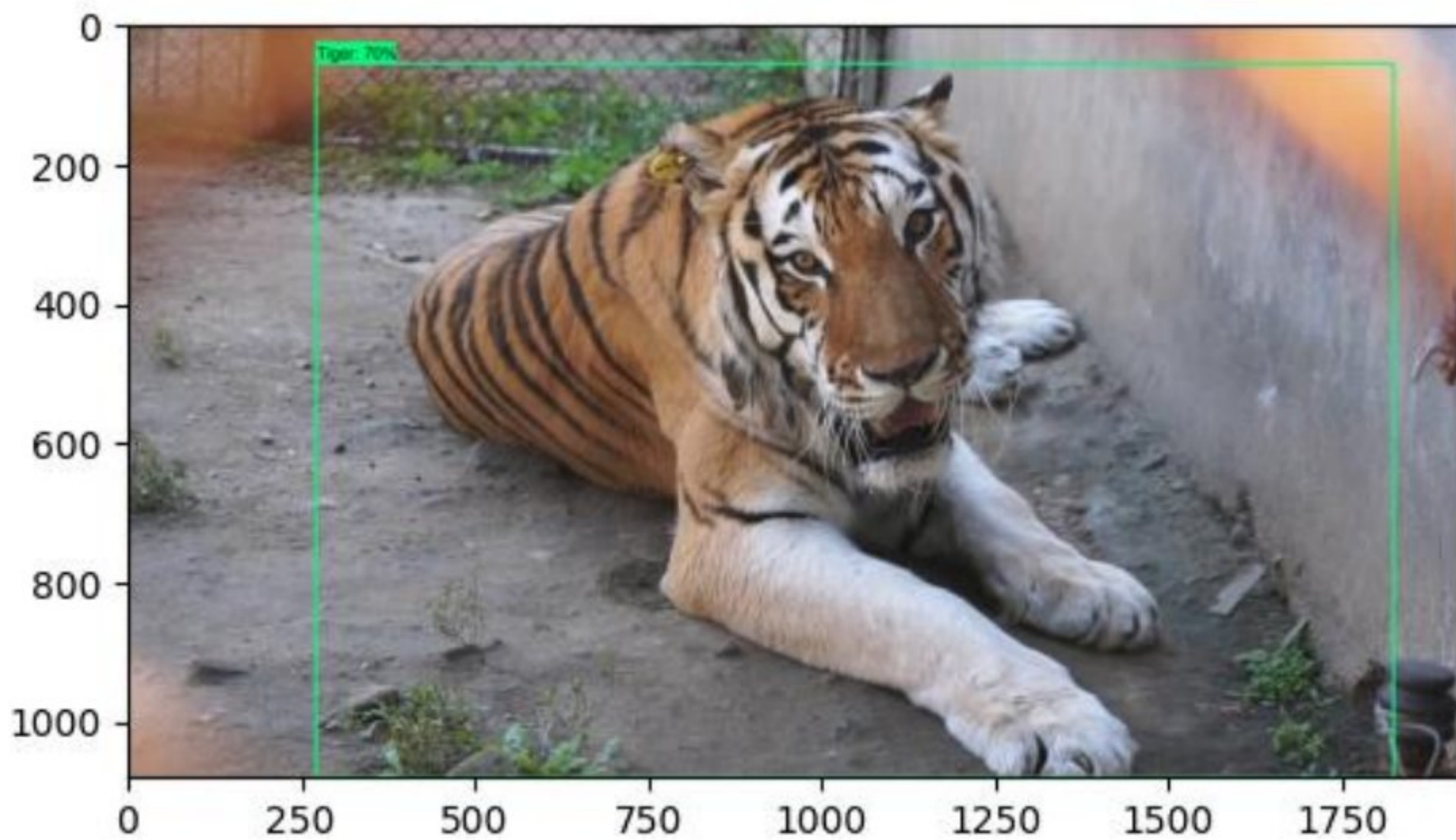
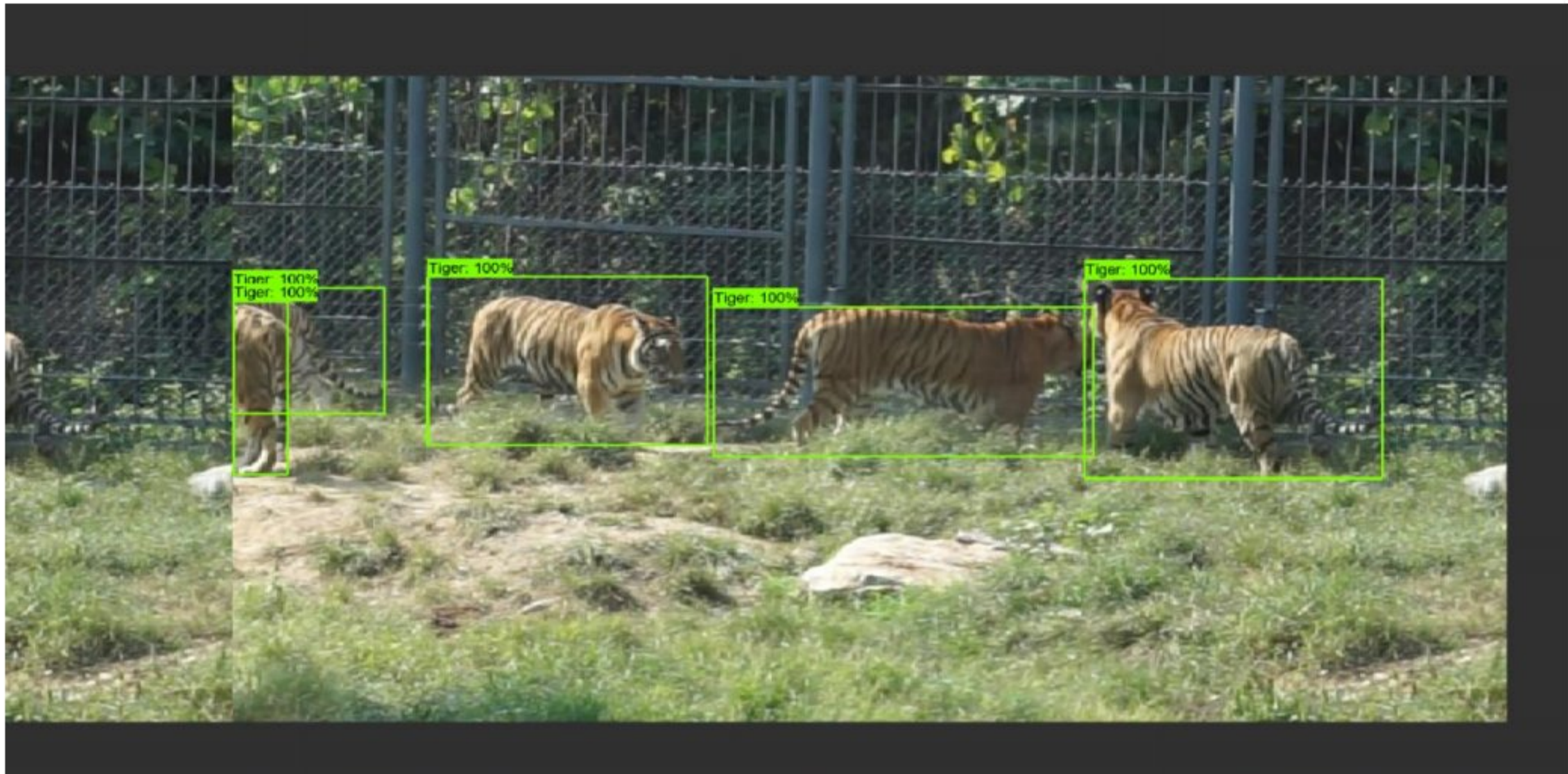


Figure 4.1 Forecast for the "Tiger" animal

This is the prediction of the animal labeled "Elephant":

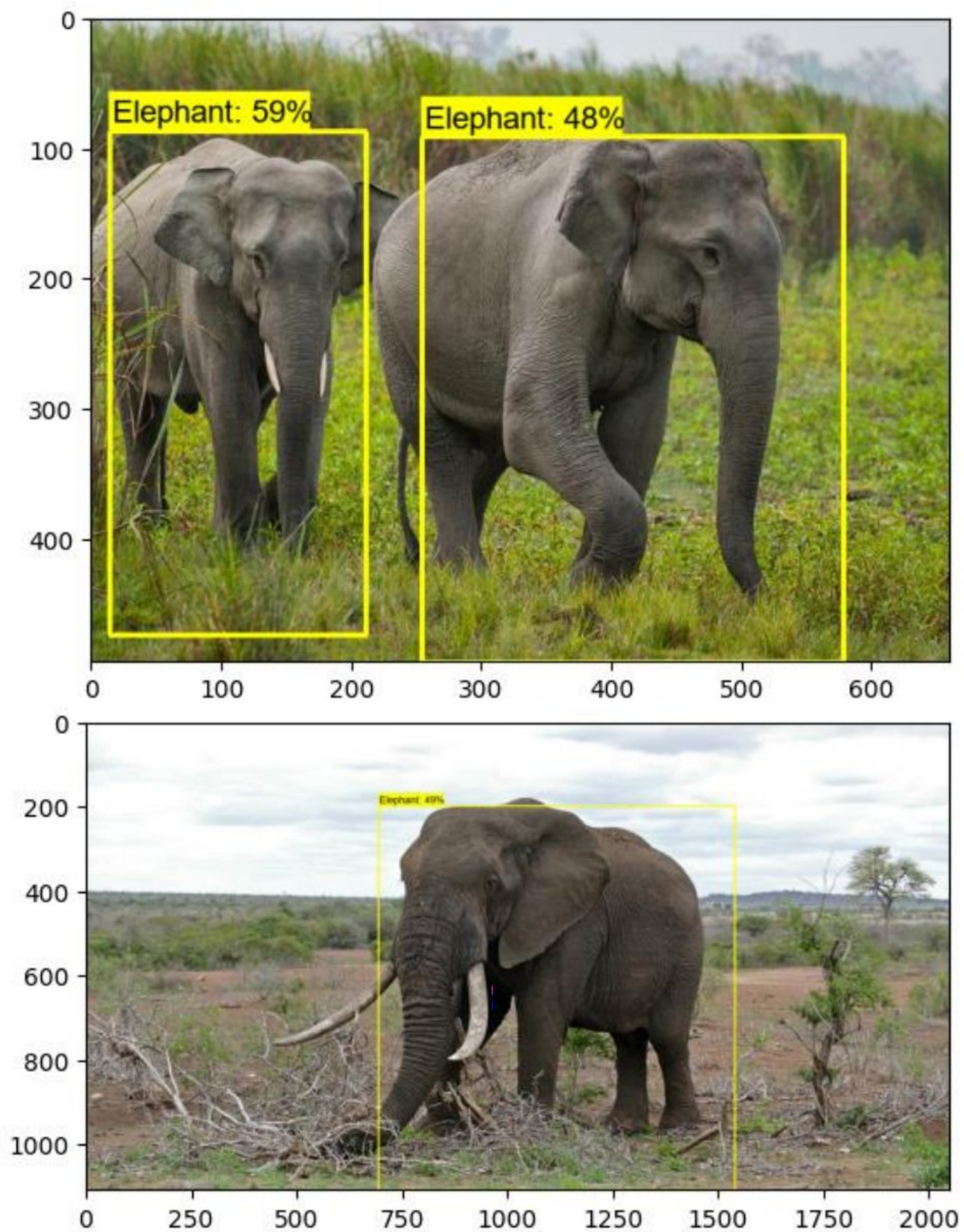


Figure 4.2 Forecast for the "Elephant" animal

This is the prediction of the label “Person”:

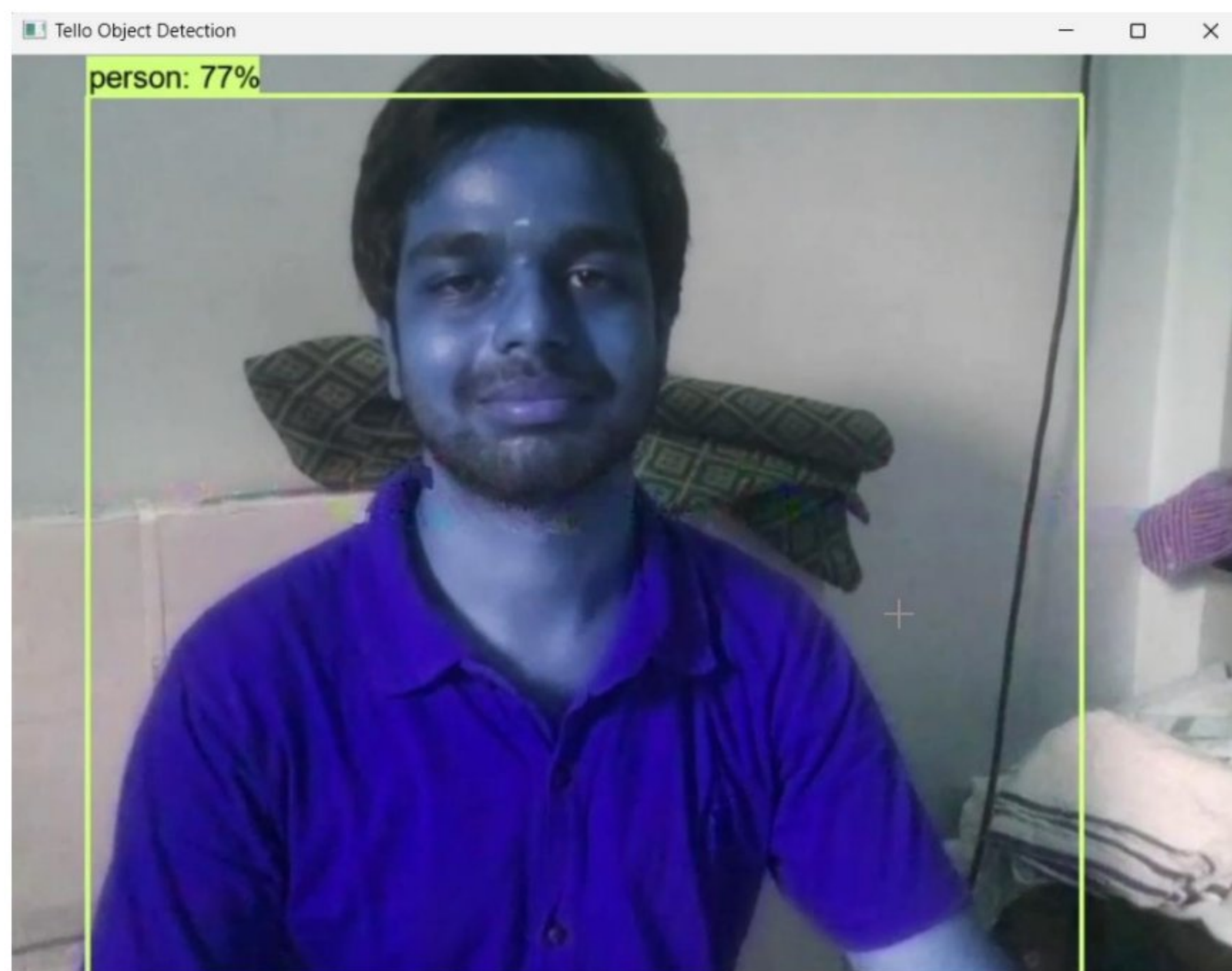
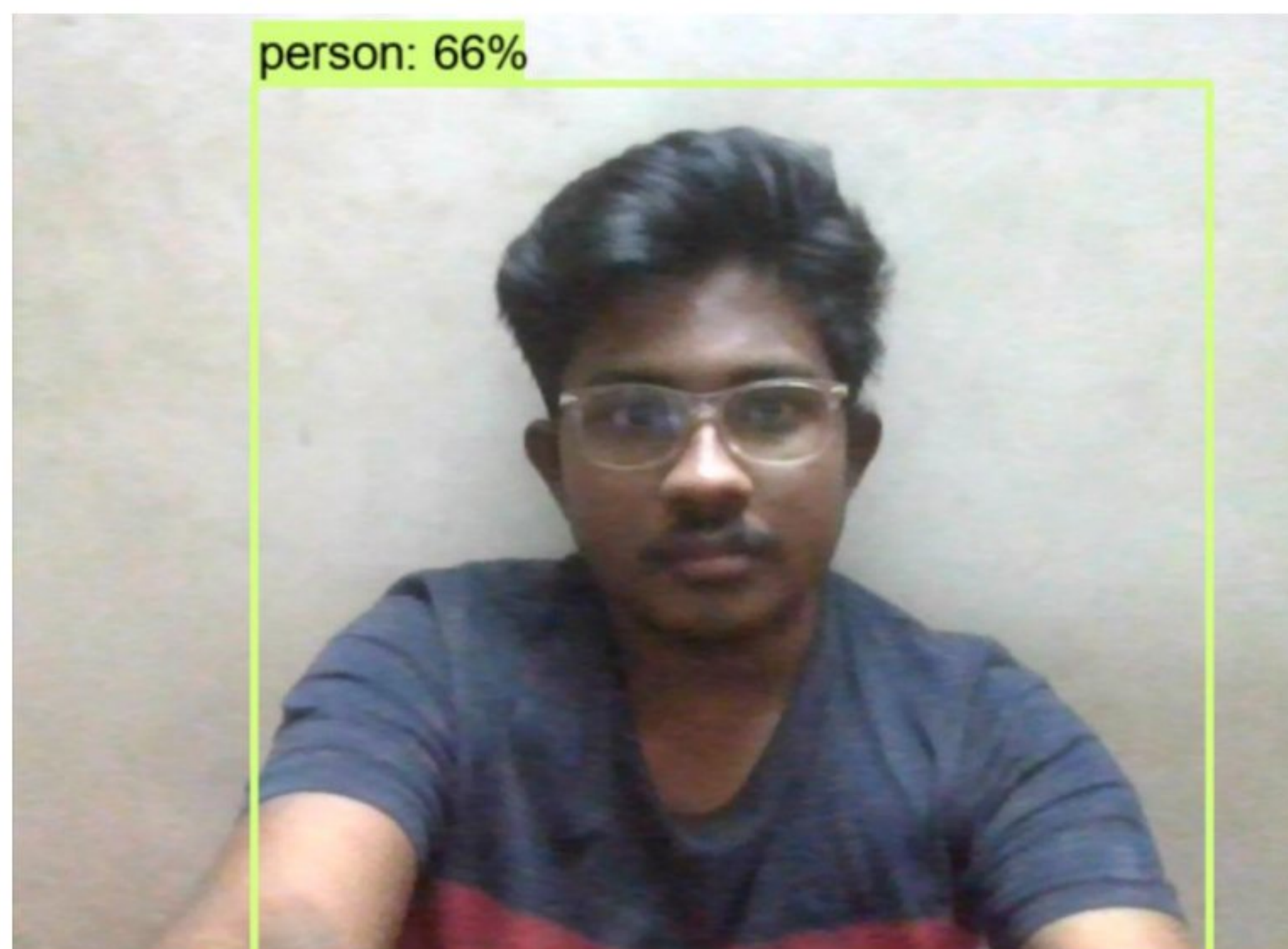


Figure 4.3 Forecast for the "Person" label

This is the prediction of the label “Knife”:

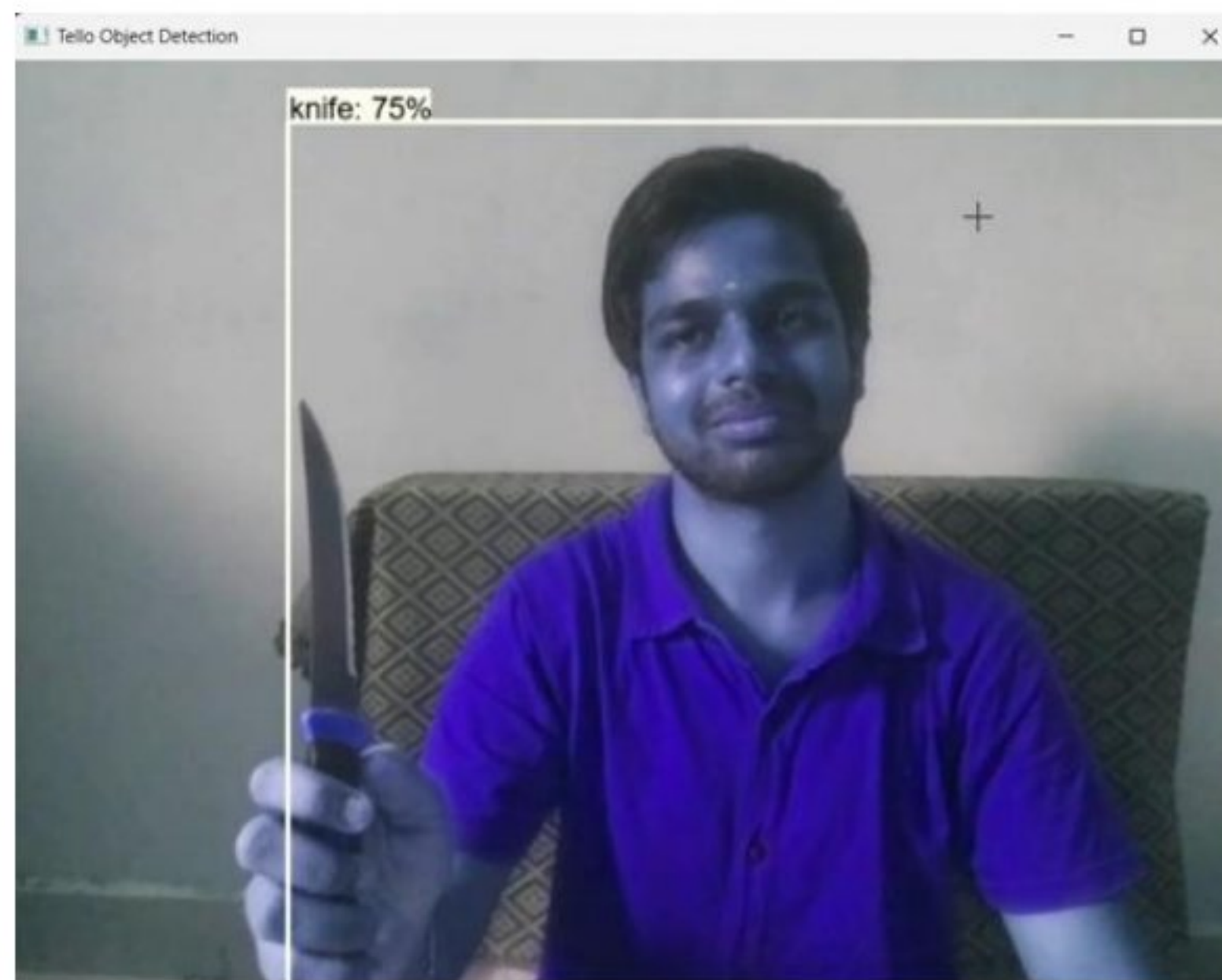


Figure 4.4 Forecast for the "Knife" label

CHAPTER-5

CONCLUSION AND FUTURE WORK

5.1 CONCLUSION

In conclusion, using ECO-WATCH GUARDIAN AI-ENHANCED drone patrols to stop poaching is a promising and successful strategy in the continuous fight to save endangered species and maintain our natural ecosystems.

With their sophisticated algorithms and real-time data analysis capabilities, the AI-enhanced drones greatly improve monitoring and poaching activity identification over large, sometimes inaccessible areas. Potential poachers are discouraged by this system's quick identification and reporting of questionable activity, which also makes it easier for law enforcement to act promptly.

5.2 FUTURE WORK

Enhancing the precision and accuracy of object detection models will continue to be a key goal in future research projects. In order to build more reliable and flexible models, this requires investigating advanced deep learning architectures, improving data augmentation approaches, and utilizing the power of transfer learning. To further attain state-of-the-art results, incorporating cutting-edge hardware solutions and optimizing model hyper parameters will be essential. The exploration of these options has the potential to increase object detection's effectiveness in a variety of applications, from autonomous vehicles to surveillance systems, ultimately boosting efficiency and safety across many industries.

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APPENDICES

A. SAMPLE CODE

```
import cv2
import numpy as np
import tensorflow as tf
from djitellopy import Tello
from object_detection.utils import label_map_util
from object_detection.utils import visualization_utils as viz_utils
import keyboard

# Load the trained detection model
detect_fn = tf.saved_model.load(r"D:\AI Drone Project\Tensorflow Object Detection
2\TFODCourse\Tensorflow\workspace\models\my_ssd_mobnet\export\saved_model"
)

# Load the label map and category index
label_map_path = r"D:\AI Drone Project\Tensorflow Object Detection
2\TFODCourse\Tensorflow\workspace\annotations\label_map.pbtxt" # Path to your
label map file
category_index =
label_map_util.create_category_index_from_labelmap(label_map_path,
use_display_name=True)

# Connect to the Tello drone
tello = Tello()
tello.connect()
tello.streamon() # Start video streaming

# Get the video stream dimensions
width = 960 # Tello video stream width
```

```

height = 720 # Tello video stream height

# Frame skip variables
frame_skip_factor = 3 # Skip every 3rd frame
frame_count = 0

# Function to handle keyboard commands
def handle_keyboard_commands():
    if keyboard.is_pressed('t'):
        tello.takeoff()
    elif keyboard.is_pressed('w'):
        tello.move_forward(30)
    elif keyboard.is_pressed('s'):
        tello.move_back(30)
    elif keyboard.is_pressed('a'):
        tello.move_left(30)
    elif keyboard.is_pressed('d'):
        tello.move_right(30)
    elif keyboard.is_pressed('q'):
        tello.rotate_counter_clockwise(30)
    elif keyboard.is_pressed('e'):
        tello.rotate_clockwise(30)
    elif keyboard.is_pressed('u'):
        tello.move_up(30)
    elif keyboard.is_pressed('j'):
        tello.move_down(30)

while True:
    frame = tello.get_frame_read().frame
    frame_count += 1

```

```

# Skip frames based on frame_skip_factor
if frame_count % frame_skip_factor != 0:
    continue
frame = cv2.resize(frame, (width, height))

# Convert frame to uint8
frame = frame.astype(np.uint8)

input_tensor = tf.convert_to_tensor(np.expand_dims(frame, 0), dtype=tf.uint8) #
Convert to uint8
detections = detect_fn(input_tensor)

num_detections = int(detections.pop('num_detections'))
detections = {key: value[0, :num_detections].numpy()
               for key, value in detections.items()}
detections['num_detections'] = num_detections

# detection_classes should be ints.
detections['detection_classes'] = detections['detection_classes'].astype(np.int64)

label_id_offset = 1
image_np_with_detections = frame.copy()

viz_utils.visualize_boxes_and_labels_on_image_array(
    image_np_with_detections,
    detections['detection_boxes'],
    detections['detection_classes'] + label_id_offset,
    detections['detection_scores'],
    category_index,
    use_normalized_coordinates=True,
    max_boxes_to_draw=5,

```

```

        min_score_thresh=.6,
        agnostic_mode=False)

    cv2.imshow('Tello Object Detection', cv2.resize(image_np_with_detections, (800,
600)))

    # Handle keyboard commands
    handle_keyboard_commands()

    if cv2.waitKey(1) & 0xFF == ord('p'):
        break

# When everything is done, release the capture and disconnect from the drone
cv2.destroyAllWindows()
tello.streamoff()
tello.disconnect()

```

B. SCREEN SHOTS

0. Setup Paths

```
[1]: import os

[2]: CUSTOM_MODEL_NAME = 'my_ssd_mobnet'
PRETRAINED_MODEL_NAME = 'ssd_mobilenet_v2_fpnlite_640x640_coco17_tpu-8'
PRETRAINED_MODEL_URL = 'http://download.tensorflow.org/models/object_detection/tf2/20200711/ssd_mobilenet_v2_fpnlite_640x640_coco17_tpu-8.tar.gz'
TF_RECORD_SCRIPT_NAME = 'generate_tfrecord.py'
LABEL_MAP_NAME = 'label_map.pbtxt'

[3]: paths = {
    'WORKSPACE_PATH': os.path.join('Tensorflow', 'workspace'),
    'SCRIPTS_PATH': os.path.join('Tensorflow', 'scripts'),
    'APIMODEL_PATH': os.path.join('Tensorflow', 'models'),
    'ANNOTATION_PATH': os.path.join('Tensorflow', 'workspace', 'annotations'),
    'IMAGE_PATH': os.path.join('Tensorflow', 'workspace', 'images'),
    'MODEL_PATH': os.path.join('Tensorflow', 'workspace', 'models'),
    'PRETRAINED_MODEL_PATH': os.path.join('Tensorflow', 'workspace', 'pre-trained-models'),
    'CHECKPOINT_PATH': os.path.join('Tensorflow', 'workspace', 'models', CUSTOM_MODEL_NAME),
    'OUTPUT_PATH': os.path.join('Tensorflow', 'workspace', 'models', CUSTOM_MODEL_NAME, 'export'),
    'TFJS_PATH': os.path.join('Tensorflow', 'workspace', 'models', CUSTOM_MODEL_NAME, 'tfjsexport'),
    'TFLITE_PATH': os.path.join('Tensorflow', 'workspace', 'models', CUSTOM_MODEL_NAME, 'tfliteexport'),
    'PROTOC_PATH': os.path.join('Tensorflow', 'protoc')
}

[4]: files = {
    'PIPELINE_CONFIG': os.path.join('Tensorflow', 'workspace', 'models', CUSTOM_MODEL_NAME, 'pipeline.config'),
    'TF_RECORD_SCRIPT': os.path.join(paths['SCRIPTS_PATH'], TF_RECORD_SCRIPT_NAME),
    'LABELMAP': os.path.join(paths['ANNOTATION_PATH'], LABEL_MAP_NAME)
}

[5]: for path in paths.values():
    if not os.path.exists(path):
        if os.name == 'posix':
            !mkdir -p {path}
        if os.name == 'nt':
            !mkdir {path}
```

1. Download TF Models Pretrained Models from Tensorflow Model Zoo and Install TFOD

```
[8]: # https://www.tensorflow.org/install/source_windows

[9]: if os.name=='nt':
    !pip install wget
    import wget

Requirement already satisfied: wget in d:\ai drone project\tensorflow object detection 2\tfodcourse\tfodj\lib\site-packages (3.2)
WARNING: Ignoring invalid distribution -rotobuf (d:\ai drone project\tensorflow object detection 2\tfodcourse\tfodj\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (d:\ai drone project\tensorflow object detection 2\tfodcourse\tfodj\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (d:\ai drone project\tensorflow object detection 2\tfodcourse\tfodj\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (d:\ai drone project\tensorflow object detection 2\tfodcourse\tfodj\lib\site-packages)
WARNING: Ignoring invalid distribution -rotobuf (d:\ai drone project\tensorflow object detection 2\tfodcourse\tfodj\lib\site-packages)
[notice] A new release of pip is available: 23.0.1 -> 23.3.2
[notice] To update, run: python.exe -m pip install --upgrade pip

[10]: if not os.path.exists(os.path.join(paths['APIMODEL_PATH'], 'research', 'object_detection')):
    !git clone https://github.com/tensorflow/models {paths['APIMODEL_PATH']}

[11]: # Install Tensorflow Object Detection
if os.name=='posix':
    !apt-get install protobuf-compiler
    !cd Tensorflow/models/research && protoc object_detection/protos/*.proto --python_out=. && cp object_detection/packages/tf2/setup.py . && python -m p

if os.name=='nt':
    url="https://github.com/protocolbuffers/protobuf/releases/download/v3.15.6/protoc-3.15.6-win64.zip"
    wget.download(url)
    !move protoc-3.15.6-win64.zip {paths['PROTOC_PATH']}
    !cd {paths['PROTOC_PATH']} && tar -xf protoc-3.15.6-win64.zip
    os.environ['PATH'] += os.pathsep + os.path.abspath(os.path.join(paths['PROTOC_PATH'], 'bin'))
    !cd Tensorflow/models/research && protoc object_detection/protos/*.proto --python_out=. && copy object_detection\packages\tf2\setup.py setup.py &&
    !cd Tensorflow/models/research/slim && pip install -e .
```

2. Create Label Map

```
[6]: labels = [{'name': 'Tiger', 'id': 1}, {'name': 'Elephant', 'id': 2}, {'name': 'person', 'id': 3}, {'name': 'knife', 'id': 4}, {'name': 'rifle', 'id': 5}, {'name': 'Z'}

with open(files['LABELMAP'], 'w') as f:
    for label in labels:
        f.write('item { \n')
        f.write('\tname: {}\n'.format(label['name']))
        f.write('\tid: {}\n'.format(label['id']))
        f.write('\n')
```

3. Create TF records

```
[7]: # OPTIONAL IF RUNNING ON COLAB
ARCHIVE_FILES = os.path.join(paths['IMAGE_PATH'], 'archive.tar.gz')
if os.path.exists(ARCHIVE_FILES):
    !tar -zxvf {ARCHIVE_FILES}

[8]: if not os.path.exists(files['TF_RECORD_SCRIPT']):
    !git clone https://github.com/nicknochnack/GenerateTFRecord {paths['SCRIPTS_PATH']}

[33]: !python {files['TF_RECORD_SCRIPT']} -x {os.path.join(paths['IMAGE_PATH'], 'train')} -l {files['LABELMAP']} -o {os.path.join(paths['ANNOTATION_PATH'], 'train.record')}
    !python {files['TF_RECORD_SCRIPT']} -x {os.path.join(paths['IMAGE_PATH'], 'test')} -l {files['LABELMAP']} -o {os.path.join(paths['ANNOTATION_PATH'], 'test.record')}

Successfully created the TFRecord file: Tensorflow\workspace\annotations\train.record
Successfully created the TFRecord file: Tensorflow\workspace\annotations\test.record
```

4. Copy Model Config to Training Folder

```
[34]: if os.name == 'posix':
    !cp {os.path.join(paths['PRETRAINED_MODEL_PATH'], PRETRAINED_MODEL_NAME, 'pipeline.config')} {os.path.join(paths['CHECKPOINT_PATH'])}
    if os.name == 'nt':
    !copy {os.path.join(paths['PRETRAINED_MODEL_PATH'], PRETRAINED_MODEL_NAME, 'pipeline.config')} {os.path.join(paths['CHECKPOINT_PATH'])}

1 file(s) copied.
```

5. Update Config For Transfer Learning

```
[8]: import tensorflow as tf
from object_detection.utils import config_util
from object_detection.protos import pipeline_pb2
from google.protobuf import text_format

[9]: config = config_util.get_configs_from_pipeline_file(files['PIPELINE_CONFIG'])

[ ]: config

[11]: pipeline_config = pipeline_pb2.TrainEvalPipelineConfig()
with tf.io.gfile.GFile(files['PIPELINE_CONFIG'], "r") as f:
    proto_str = f.read()
    text_format.Merge(proto_str, pipeline_config)

[12]: pipeline_config.model.ssd.num_classes = len(labels)
pipeline_config.train_config.batch_size = 8
pipeline_config.train_config.fine_tune_checkpoint = os.path.join(paths['PRETRAINED_MODEL_PATH'], PRETRAINED_MODEL_NAME, 'checkpoint', 'ckpt-0')
pipeline_config.train_config.fine_tune_checkpoint_type = "detection"
pipeline_config.train_input_reader.label_map_path = files['LABELMAP']
pipeline_config.train_input_reader.tf_record_input_reader.input_path[:] = [os.path.join(paths['ANNOTATION_PATH'], 'train.record')]
pipeline_config.eval_input_reader[0].label_map_path = files['LABELMAP']
pipeline_config.eval_input_reader[0].tf_record_input_reader.input_path[:] = [os.path.join(paths['ANNOTATION_PATH'], 'test.record')]

[13]: config_text = text_format.MessageToString(pipeline_config)
with tf.io.gfile.GFile(files['PIPELINE_CONFIG'], "wb") as f:
    f.write(config_text)
```

6. Train the model

```
[14]: TRAINING_SCRIPT = os.path.join(paths['APIMODEL_PATH'], 'research', 'object_detection', 'model_main_tf2.py')

[15]: command = "python {} --model_dir={} --pipeline_config_path={} --num_train_steps=2000".format(TRAINING_SCRIPT, paths['CHECKPOINT_PATH'], files['PIPELINE_CONFIG'])

[17]: print(command)

python Tensorflow\models\research\object_detection\model_main_tf2.py --model_dir=Tensorflow\workspace\models\my_ssd_mobnet --pipeline_config_path=Tensorflow\workspace\models\my_ssd_mobnet\pipeline.config --num_train_steps=2000

[ ]: !{command}
```

7. Evaluate the Model

```
[17]: command = "python {} --model_dir={} --pipeline_config_path={} --checkpoint_dir={} ".format(TRAINING_SCRIPT, paths['CHECKPOINT_PATH'], files['PIPELINE_CONFIG'], paths['CHECKPOINT_PATH'])

[18]: print(command)

python Tensorflow\models\research\object_detection\model_main_tf2.py --model_dir=Tensorflow\workspace\models\my_ssd_mobnet --pipeline_config_path=Tensorflow\workspace\models\my_ssd_mobnet\pipeline.config --checkpoint_dir=Tensorflow\workspace\models\my_ssd_mobnet

[22]: !{command}

^C
```

8. Load Train Model From Checkpoint

```
[16]: import os
import tensorflow as tf
from object_detection.utils import label_map_util
from object_detection.utils import visualization_utils as viz_utils
from object_detection.builders import model_builder
from object_detection.utils import config_util

[17]: # Load pipeline config and build a detection model
configs = config_util.get_configs_from_pipeline_file(files['PIPELINE_CONFIG'])
detection_model = model_builder.build(model_config=configs['model'], is_training=False)

# Restore checkpoint
ckpt = tf.compat.v2.train.Checkpoint(model=detection_model)
ckpt.restore(os.path.join(paths['CHECKPOINT_PATH'], 'ckpt-3')).expect_partial()

@tf.function
def detect_fn(image):
    image, shapes = detection_model.preprocess(image)
    prediction_dict = detection_model.predict(image, shapes)
    detections = detection_model.postprocess(prediction_dict, shapes)
    return detections
```

10. Freezing the Graph

```
[36]: FREEZE_SCRIPT = os.path.join(paths['APIMODEL_PATH'], 'research', 'object_detection', 'exporter_main_v2.py ')

[37]: command = "python {} --input_type=image_tensor --pipeline_config_path={} --trained_checkpoint_dir={} --output_directory={} ".format(FREEZE_SCRIPT, files['PIPELINE_CONFIG'], paths['CHECKPOINT_PATH'], paths['EXPORT_PATH'])

[38]: print(command)

python Tensorflow\models\research\object_detection\exporter_main_v2.py --input_type=image_tensor --pipeline_config_path=Tensorflow\workspace\models\my_ssd_mobnet\pipeline.config --trained_checkpoint_dir=Tensorflow\workspace\models\my_ssd_mobnet --output_directory=Tensorflow\workspace\models\my_ssd_mobnet\export

[39]: !{command}
```

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PAPER REVIEW FORM	
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Eco-Watch Guardian AI-Enhanced Drone Patrols against Poaching

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Abstract - Conservationists are searching for cutting-edge technical solutions in response to the growing problem of poaching and its catastrophic effects on animal populations. Drones and other names for unmanned aerial vehicles, have shown promise as a tool for wildlife monitoring and anti-poaching operations in recent years. Drone data can be analyzed to provide important insights into animal behavior, migration patterns, and habitat conditions, assisting in the development of more informed conservation strategies. Since the device does not hurt the species being attacked but rather causes discomfort that results in spontaneous pull it is technologically more sophisticated. In order to ensure that the volume patterns of successive frames remain coherent across time, the graph regularized is applied to them. Equipped with various navigation systems such as the GPS and optical flow, they are able to practically navigate itself thanks to today's fly-by-wire technique. Among the many possible uses for drones in tandem with other technology include soil inspections and satellite surveillance. Additionally, the integration of artificial intelligence and machine learning algorithms improves the drone's ability to identify and differentiate between poachers and legitimate visitors or researchers.

Keywords – Animal poacher detection, TensorFlow, MobileNet SSD, deep learning, real-time recognition, wildlife conservation.

I. INTRODUCTION

The incorporation of unmanned aerial vehicles (UAVs), sometimes called drones, have showed potential as a tool for anti-poaching and wildlife monitoring actions. An overview of the use of drone monitoring in avoiding poaching and conserving wildlife is presented here. Drones can quickly cover large, inaccessible areas and provide immediate surveillance to detect threats and monitor animal populations. "Drones" may be classed in different ways, such as according to their intended application, such as drones for shooting.

Unmanned aerial vehicles (UAVs) have many potential applications, including surveillance and mapping efforts. But the easiest approach to categorize "drones" is based on platforms in the air. Many fly at scaled speeds that are competitive with human airplanes and are fueled by small gas engines, some even turbines. Due to the complexity of their control systems, multi-rotor UAVs vary from helicopters in that a computer is required to handle control input. Usually are just propellers instead of a rudder or an aileron, unlike in aircraft. Drones can spot poachers regardless of how they are

disguised by darkness or dense foliage thanks of their high resolution cameras, infrared imaging, and sophisticated sensors, enabling law enforcement to respond rapidly. A significant advance in methods for conservation is the use of drone monitoring for anti-poaching and wildlife preservation.

Poaching presents a major danger to many species across the globe, driving several to the edge of destruction. Traditional conservation efforts have encountered difficulty tracking down broad and isolated regions where poaching typically occurs. Algorithms based on machine learning allow the system to discriminate between people, cars, and animals, lowering false alarms and enhancing the accuracy of danger detection. Drones cover broad regions fast, decreasing the time necessary for manned patrols and boosting the overall efficiency of conservation activities. The abundance of data acquired by the drones helps decision-making based on evidence, supporting conservationists in understanding and managing concerns about the environment.

The issue of the poaching of wildlife presents a major threat to the delicate balance of ecosystems and the existence of countless endangered species. In reaction to this critical conservation dilemma, the integration of drone technology has emerged as a strong instrument in the battle against poaching operations. This novel strategy not only harnesses the benefits of airborne observation but also combines innovative elements to boost efficiency, accuracy, and the overall effect of animal conservation activities. Wildlife poaching, fueled by illegal markets for animal products and environmental degradation, is a serious concern internationally. The constant pursuit of ivory, rhino horns, and other valued components of mammals has contributed to the extinction of iconic species and disturbed ecosystems. Recognizing the necessity of conservation, drone patrols have become an indispensable tool in the panoply of tactics aimed at protecting biodiversity.

While drone patrols have showed efficacy in curtailing poaching, problems including as legislative applications, privacy issues, and the need for coordination between governments, conservation groups, and local populations persist. Future developments in drone technology, like

greater travel periods, higher battery economy, and upgraded AI algorithms, offer promise for even more effective anti-poaching tactics. The delicate balance of ecosystems is increasingly under threat from forces such as worldwide warming, forest loss, and trafficking. Traditional conservation approaches, although necessary, suffer constraints in monitoring huge and distant regions in real-time. The Eco-Watch Guardian AI-Enhanced system tackles these constraints by using sophisticated technology to develop a dynamic and responsive approach to environmental protection.

II. RELATED WORK

[i] A technique that uses vision to guide unmanned aerial vehicles (UAVs) is presented by the work of K. Kim, J. Kim, H. -G. Lee, J. Choi, J. Fan, and J. Joung (2023) and may protect a pursuer UAV (pUAV) from evader UAVs. The suggested UAV chasing system generates control signals and tracks UAVs. The proposed UAV detecting method combines a deep learning-based object detector, you only look once version three (YOLOv3), and existing object monitors to improve pUAV tracking in a cheap processor complex. The object identification system may be linked with the object tracker, which localizes the objects or provides the complete region occupied by the place at any precise moment. [1].

[ii] In their study, P. Zhu, T. Peng, D. Du, H. Yu, L. Zhang, and Q. Hu (2021) proposed A massive video based animal species calculating collection for agricultural and wildlife conservation named Animal Drone. Artificial intelligence (AI) is fast increasing because it has been successfully employed in a broad variety of areas, including the industrial and automotive industries. It's also exciting to watch how AI integrates with protection of wildlife and agriculture. The dataset is separated into two parts: the first portion, which was gathered from on-site drone video, and Part-B, which was obtained from internet sources. Both portions include detailed 53,644 shots with the annotation of almost 4 million objects and relevant characteristics like weight, altitude, and perspective. Despite tremendous progress over the last several years, counting animals with drones is still challenging due of a number of difficulties, including motion blur, scale

fluctuation, a lack of positive sample size, and tiny things. In order to build animal tracking systems using drones, there are currently no publicly accessible massive data sets or references. Even though bat, penguin, and elephant counting databases exist their data quantities, animal species, and situations they cover are still confined. The issue of reciprocal obstruction between humans in a big density group in flat view observation may be overcome by drones' precise vision. Drones are thus great for tracking creatures. Over 4 million items are labeled in 53,644 frames across a range of contexts in Animal Drone. The dataset for animals from drones covers 10 distinct species.

III. PROPOSED SYSTEM

The suggested Eco-Watch Guardian AI-Enhanced Drone Patrols provide a groundbreaking way to tackle the continuous menace of illegally harvesting wildlife. By blending state-of-the-art artificial intelligence with modern drone technology, this system is aimed to offer an anticipatory, efficient, and physically resilient solution to the complex issues connected with safeguarding endangered species and their ecosystems. The rising issues faced by environmental changes, habitat degradation, and natural catastrophes, a suggested system employing drone technology promises to modernize monitor the environment. This unique system, built for extensive gathering and interpreting of data, meets the rising demand for updated data to support conservation initiatives, disaster response, and efficient use of resources.

3.1 ARCHITECTURE

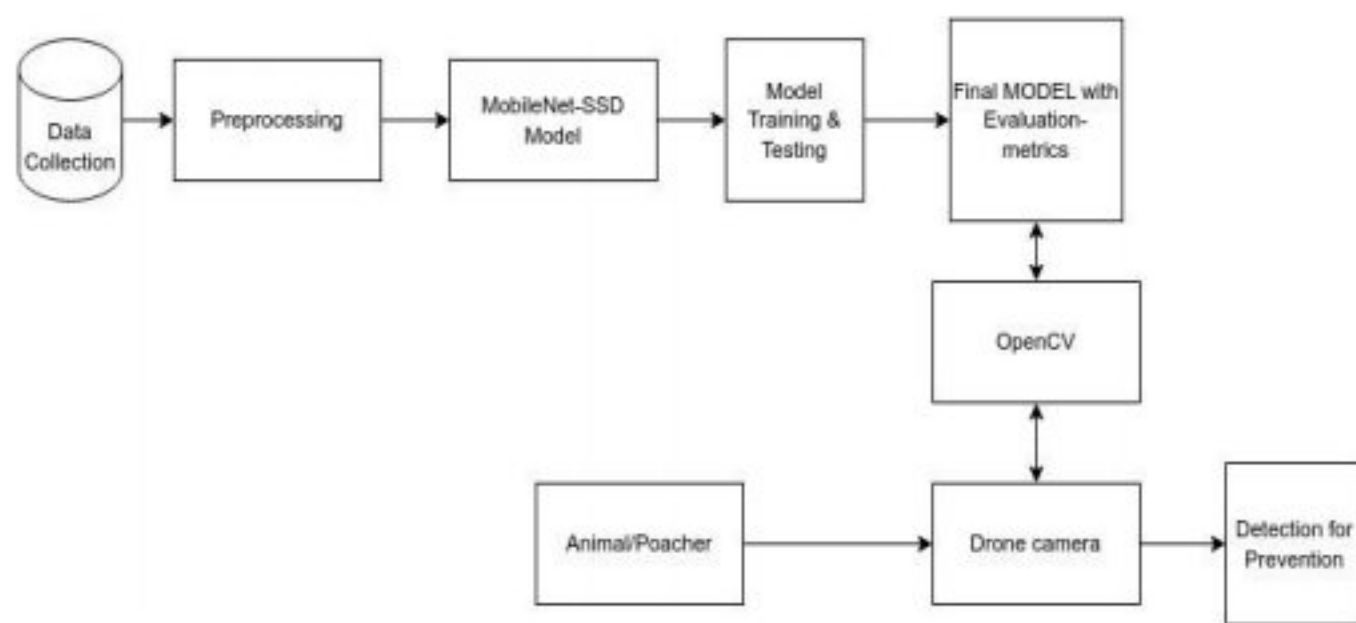


Fig 1 Model Architecture

The architecture proposed for animal poacher detection utilizing a TensorFlow model involves a multi-stage process that integrates advanced deep

learning techniques. The first stage of the architecture comprises a comprehensive dataset collection, including images from various wildlife habitats and potential poaching scenarios. This dataset is then preprocessed to enhance image quality and standardize features.

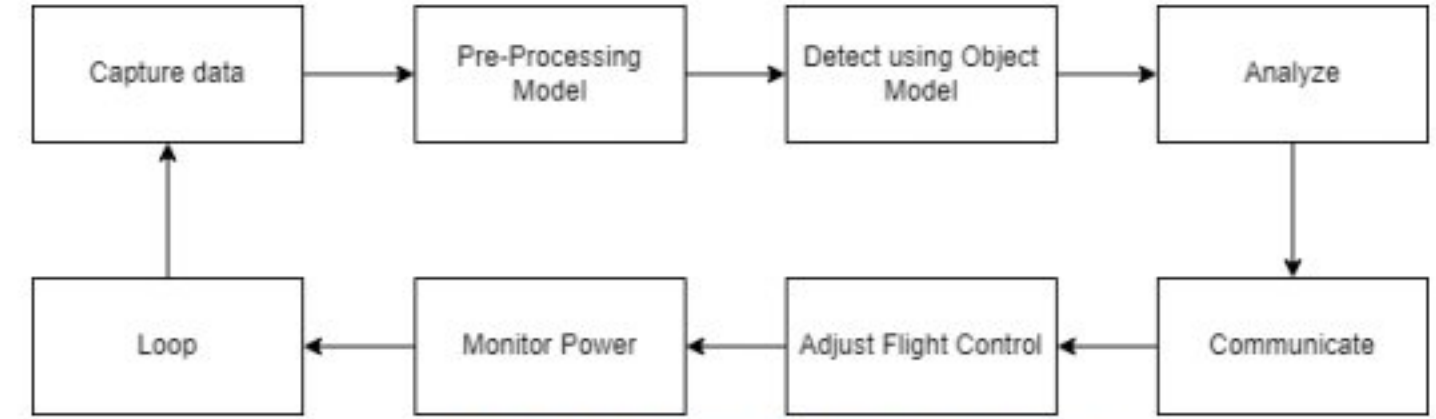


Fig 2 System Architecture

The core of the architecture relies on a Convolutional Neural Network (CNN) implemented through Tensor Flow, a powerful open-source machine learning framework. The CNN is specifically designed to extract intricate features from wildlife images, allowing the model to discern potential threats and identify distinct patterns associated with poaching activities. The method of transfer learning is applied by using models that have been trained before, allowing the network to exploit information obtained from large-scale picture datasets. To enhance the model's performance and simplify detection in real-time, the architecture incorporates a streamlined inference pipeline. This involves deploying the trained TensorFlow model on edge devices or cloud platforms, ensuring efficient processing of incoming data streams.

In conclusion, the proposed architecture for animal poacher detection employing a TensorFlow model is a comprehensive solution that combines advanced deep learning techniques, transfer learning, and geospatial data integration. This holistic approach aims to enhance the accuracy and reliability of poacher detection systems, contributing to the conservation of endangered wildlife populations.

3.2 METHODOLOGY

The methodology for the research paper on animal poacher detection using a TensorFlow model involves a systematic approach encompassing data collection, preprocessing, model development, training, and evaluation. The following outlines the key steps in the methodology:

- **Dataset Collection:** Gather a diverse dataset containing images of wildlife habitats, animals, and potential poaching scenarios. Include images from various sources, such as camera traps, satellite imagery, and open-access wildlife databases. Annotate the dataset with labels indicating the presence or absence of poaching activities. Include multiple classes to capture different types of poaching behaviors.
- **Data Preprocessing:** Standardize the dataset by resizing images to a consistent resolution, ensuring uniformity for model training. Apply image augmentation techniques to enhance the variety of the used for training the database while strengthening generalization of models. Normalize pixel values to a common scale to facilitate convergence during training.
- **Model Development:** Choose a pre-trained CNN architecture from TensorFlow's model zoo (Mobile-net SSD) as the base model for feature extraction. Integrate the CNN Using recurrent neural networks (RNNs) networks to records spatial connections in natural events. Add additional layers for classification, adapting the model to identify poaching-related patterns.
- **Training:** Dividing the data collection into learning, validation, while examining establishes to train and assess the accuracy of the model. Utilize TensorFlow's training APIs to optimize the model's weights using back propagation and stochastic gradient descent. Monitor the training process, adjusting hyper parameters if necessary to prevent over fitting or under fitting.
- **Evaluation:** Assess the model's efficiency using measures like as reliability, recall, F1 score, and consistency on the test set. Conducting ablation experiments to examine the influence of many different aspects of the framework on its overall effectiveness. Compare the proposed model against baseline models or existing poacher detection systems to demonstrate its effectiveness.

By following this comprehensive methodology, the research aims to develop an effective and

ethically sound animal poacher detection system using TensorFlow, contributing to wildlife conservation efforts.

3.3 IMPLEMENTATION

The implementation of the proposed animal poacher detection system involves coding and deploying the methodology described. Below is a simplified outline of the steps you might follow for the implementation using TensorFlow.

- **System Architecture:** The proposed system architecture is designed to seamlessly integrate various components, ensuring a robust and efficient pipeline for animal poacher detection.
- **Data Collection and Preprocessing:** The system begins with the collection of diverse datasets containing images and videos from wildlife reserves and natural habitats. The preprocessing stage involves data cleaning, augmentation, and annotation to enhance the model's ability to generalize across different scenarios. Geographic information system (GIS) data may be incorporated to provide spatial context.
- **Model Development:** The core of the system is based on the TensorFlow MobileNet SSD (Single Shot Multibox Detector) architecture. MobileNet SSD is chosen for its lightweight design, making it suitable for real-time apps on gadgets with limited resources. The model is adapted to the specific requirements of animal poacher detection, considering factors such as
- video feeds obtained from various sources, including wildlife reserves, surveillance cameras, and unmanned aerial vehicles (drones). The integration process involves optimizing the model specifically for inference on both mobile devices and drones, ensuring low latency and real-time responsiveness.

3.4 OUTCOMES

The outcomes of the animal poacher detection project utilizing the described system architecture can be diverse and impactful. Here are potential outcomes that the project may achieve:

- **Improved Poaching Detection Accuracy:** The

primary goal is to achieve a high level of accuracy in detecting poaching activities through the integration of advanced deep learning techniques. This outcome would contribute significantly to wildlife conservation efforts.

- **Real-time Monitoring and Intervention:** With the integration of the model into a drone platform, the project aims to provide real-time monitoring of wildlife habitats. This capability enables timely intervention and response to potential poaching incidents, enhancing the effectiveness of conservation strategies.
- **Geospatial Insights for Conservation Planning:** The incorporation of geospatial data enhances the model's ability to provide insights into the spatial distribution of poaching incidents. Conservationists can use this information to plan targeted interventions and prioritize areas for conservation efforts.
- **Enhanced Wildlife Population Monitoring:** The project may contribute to broader wildlife population monitoring efforts. By analyzing images and data collected over time, conservationists can gain insights into animal behaviors, migration patterns, and population trends.

Overall, the project outcomes are aimed at leveraging technology to address the critical issue of animal poaching, with the ultimate goal of making a positive impact on wildlife conservation and biodiversity preservation. Conservationists can use this information to plan targeted interventions

IV. RESULTS AND DISCUSSION

The project has demonstrated encouraging outcomes, signifying a noteworthy advancement in the development of inclusive technologies that enhance animal conservation in diverse domains.

- **Adaptive Learning and Improved Performance:** The system demonstrated continuous improvement in poacher recognition accuracy over time, showcasing its ability to evolve based on user interactions. This adaptive learning contributes to sustained and enhanced performance.
- **Robust Adaptation to Real-World**

Challenges: The project successfully adapted to variations in wildlife habitats, lighting conditions, and poaching scenarios, highlighting its robustness in real-world applications. The system's adaptability ensures effectiveness in diverse environmental conditions and poaching tactics.

- **Efficient Real-Time Detection:** The system consistently achieved real-time responses within specified criteria, meeting practical use standards. This efficiency allows timely interventions and rapid responses to potential poaching incidents. An in-depth examination of recognition errors provides valuable insights, guiding future enhancements to address identified weaknesses.

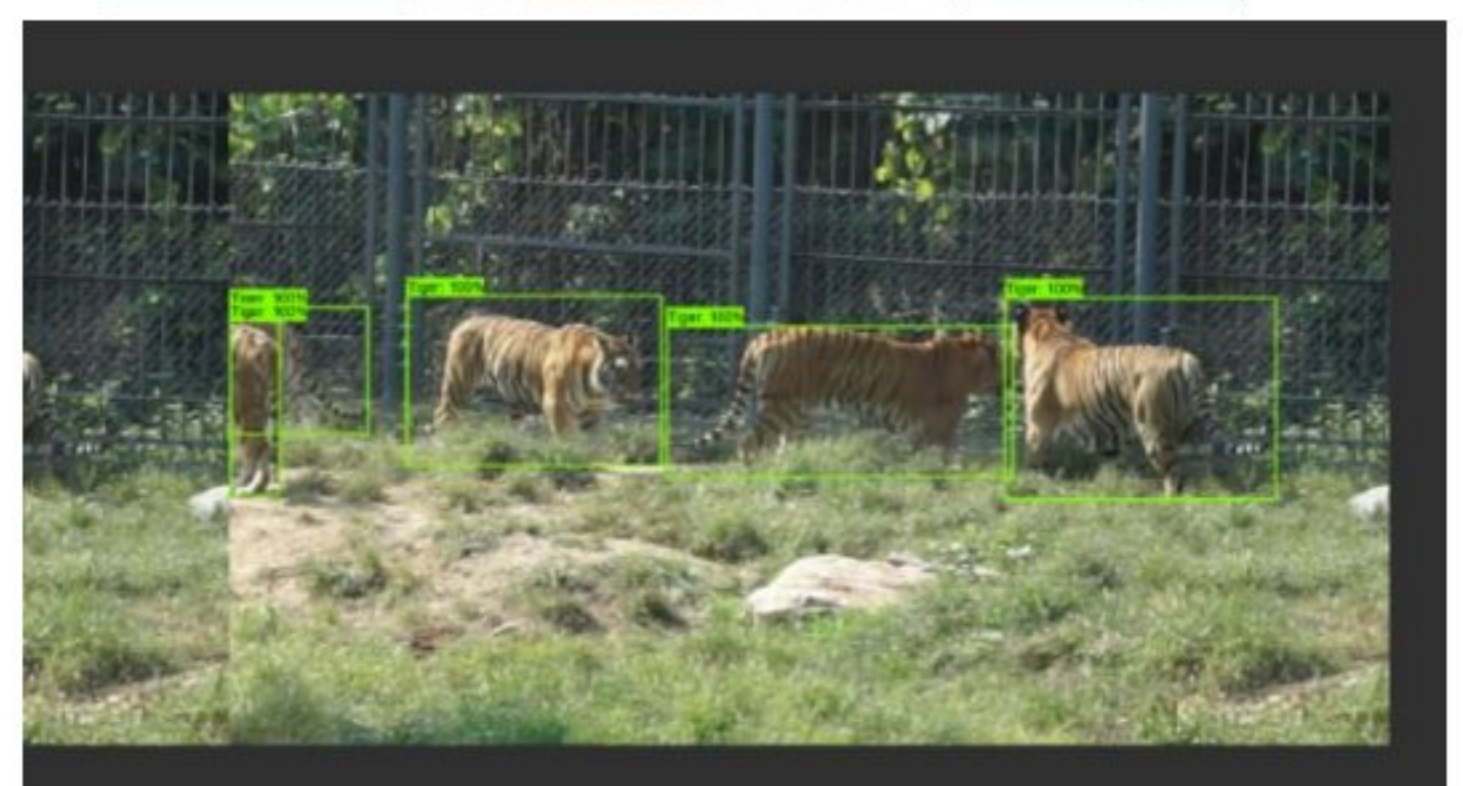


Fig 3 Output Screenshots

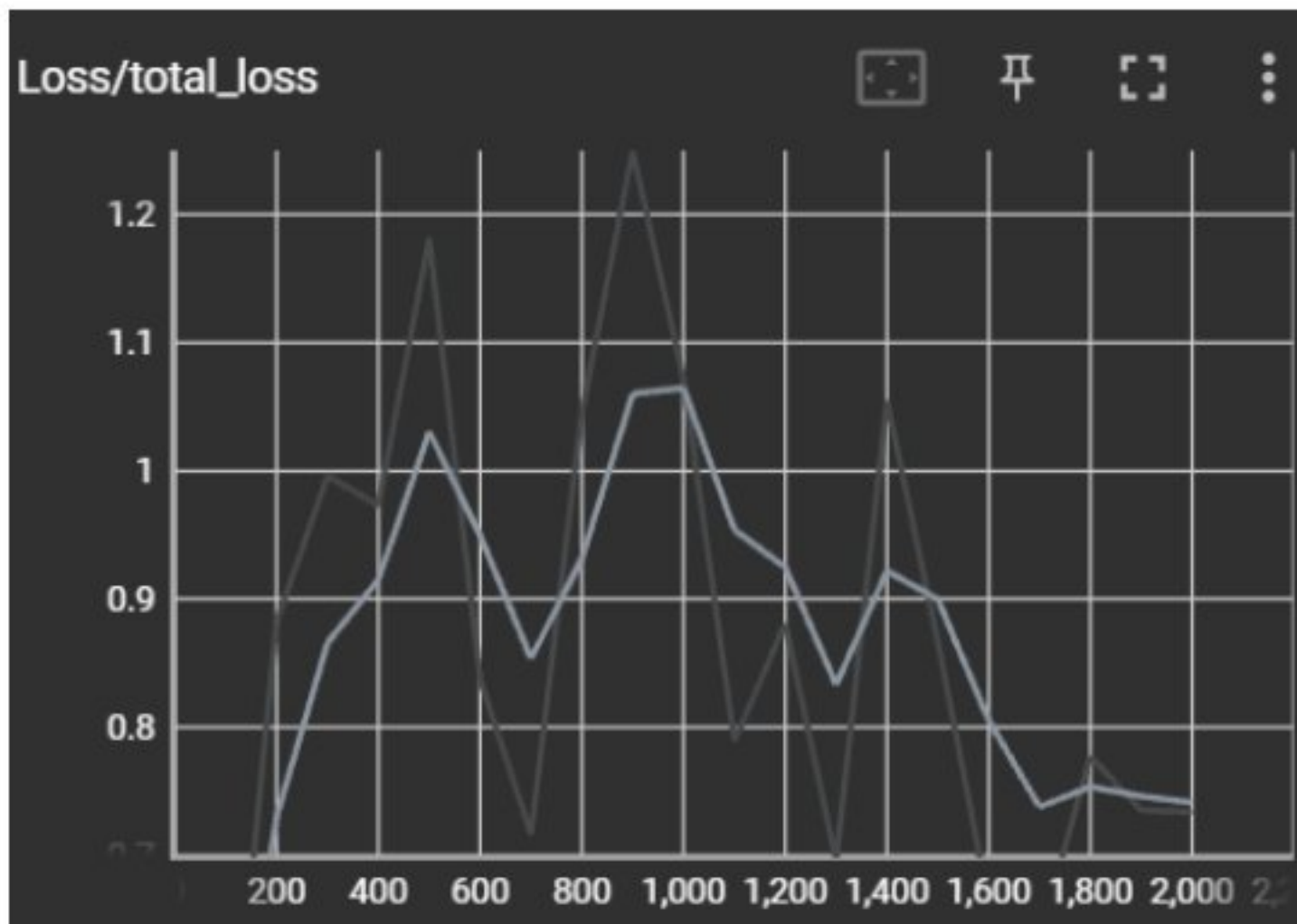


Fig 4 Loss Graph

Measurements of latency were made during real-time recognition, and the system consistently produced results that satisfied the requirements for practical application. A comprehensive analysis of recognition mistakes yielded insights into particular issues, directing future improvements and updates to rectify found shortcomings.

V. CONCLUSION

In conclusion, the animal poacher detection project has achieved notable success in leveraging advanced technologies for wildlife conservation. The implementation of adaptive learning mechanisms demonstrated a consistent improvement in recognition accuracy over time, showcasing the system's ability to evolve based on user interactions. This adaptability contributes to sustained and enhanced performance, reinforcing the project's potential as a valuable tool for addressing the complex challenges of poaching in diverse wildlife habitats.

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