# Sensitivity of Robot-Aided Remote Object Detection in Forests under Variation of Light Illumination

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**Abstract**

Forests degradation and deforestation are increasingly becoming a risk to the world's ecosystem with major effects on climate change. Mitigating these dangers is tackled through reliable management of monitoring tree species, insect infestations and wildlife behaviour. Although forest rangers can use artificial intelligence and machine learning techniques to analyse forest health through visionary sensing, exploring the accuracy of object detection under low illuminations such as sunsets, clouds or below dense forest canopy is often ignored. In this paper, we have investigated the importance of illumination on detection through a high definition GoPro9 camera as compared to the low-cost RaspberryPi camera. An external sensing platform accommodated by a quadruped robot is developed to carry the hardware, one of the first implementations of autonomous system in forest health monitoring. The compound-scaled object detection, YOLOv5s model pretrained on COCO dataset containing 800,000 instances, used for person detection, is retrained on custom dataset to detect forest health indicators such as burrows and deadwood. The system is tested and evaluated under various lighting conditions to detect objects located at various distances from the vision sensors. This study concludes that YOLOv5s model can detect a person and forest health indicators up to a distance of 10m with accuracy of 67% and 51% respectively at dusk which shows that light exposure has a major effect on detection performance. Furthermore, the quadruped robot carrying the sensing platform managed to successfully shift between different positions while carrying out the detection.

**Keywords**

YOLOv5, Quadruped Robot, Forest Health Indicators, RPi, GoPro9

## 1. Introduction

Over the past decade, the forests' health has been deteriorating due to climate change, air pollution, and deforestation. Forest management and Forest ecological research observe many forest health indicators (FHI) such as insects infestations, wildlife signs, tree species and deadwood to support in monitoring the forests health [1]. The forest surveying tasks can be accelerated by leveraging autonomous vehicles such as robots equipped with computer vision and machine learning technologies [2]. Mobile robots have immensely advanced into attracting the attention of users of different disciplines worldwide. In-depth research on these robots using artificial intelligence (AI) such as image classifications, and object detection has enabled them to become applicable for many applications that include complex environments, rescue operations, monitoring, indoor tracking, outdoor tracking, policing and many more [3]. While these vehicles are uniquely developed to support human operations or carry out certain tasks that are non-reachable by a person, the operational outcomes achieved thus far with multi-model visionary sensing and AI has resulted in the advancement of further autonomy through smart computing platforms.

In terms of ground robots, these can be broadly classified into three categories: wheeled robot, tracked robot and quadruped robot [4]. The category that is generally selected by the operator is based on the set application and its environments. Due to the fact that this paper is focused on evaluating the detection of certain objects within the forest, the quadruped robot was selected for this study because of the uneven terrain and the lack of wheeled robots that can navigate through trees, branches and muddy areas.

The authors in [5] promotes quadruped robots in working within dangerous and unreachable environments. Other researchers have also explored the gait motions of the robot through adaptive control algorithms, such that the operational lifetimes can be improved by enabling smart adaptability through different environments [6], [7]. Another research group have also explored the advancements in robotics within forestry environments [8]. Hence, Quadruped robots are found to be most applicable for monitoring in the forest as they do not require consistent ground contacts [9]. This makes them particularly

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useful as they can surpass logs, branches, twigs and soft lands successfully. Although these vehicles are vastly being implemented for many applications, there is currently a lack of research into implementing them within native forests. Hence this paper highlights an approach of using a unique robot to collect data from the forest, which can be suitable within different sites to support the forest ranger.

A variety of object detection algorithms have been proposed with the recent advancement in deep learning. The most popular object detection algorithms are GPU-accelerated and Convolutional Neural Networks (CNN) deep learning frameworks. For the CNN-based object detectors, the number of classes can can range up to a few thousand for training. These algorithms can be roughly categorised as: two-staged and single-staged. The two-staged object detection algorithms are Faster R-CNN [10], Fast R-CNN [11], Region Based Fully CNN (R-FCN) [12], and Regions-Based CNN (R-CNN) [13]. R-CNN is the first real target detection CNN-based model that achieves a mean average precision (mAP) of 66%. Single-staged object detection algorithms include Single Shot Detector (SSD) [14] and You Only Look Once (YOLO) [15] series, i.e. YOLOv1, YOLOv2, YOLOv3, YOLOv4, and YOLOv5.

Under ideal conditions of target visibility, a high detection accuracy can be achieved using these algorithms. However, adverse visual conditions such as low light illumination, rain, fog, and snow extremely degrade the performance of object detection models. Evidently, the importance of camera-based object detection is very high in critical situations such as vehicle safety, construction object detection, and search and rescue. In this regard, the authors in [16], reviewed the state-of-art technologies to address the problem of object detection under rainy conditions for autonomous vehicles. They combined the Deraining [17] and Image Translation [18] techniques with Faster R-CNN and YOLOv3 algorithms for mitigating the influence of rainy conditions. The comparison of detection accuracy shows that the performance of these algorithms deteriorates after feeding derained images. This is because the process of deraining smooths out the input image with a loss of meaningful information and distinctive scene features. For instance, The authors of [19] found that the YOLOv3 model significantly outperformed YOLOv2 with the mean Average Precision (mAP) of 78.2% for detecting construction vehicles under different visualisations. Similarly, due to limited availability of weather image data, the researchers in [20] used Generative Adversarial Networks (GAN) to generate realistic-looking weather effects for the rain, fog and snow. These data can be used for object detection under poor visible conditions, which can help in improving the algorithms performance.

The network structure of YOLOv5's is similar to any other YOLO series in terms of components, i.e. Input, Backbone and Neck. It functions similar to its predecessor algorithms where the backbone network consists of PyTorch rather than Darknet. The Input in YOLOv5 uses adaptive anchor frame calculation that adaptively gives the optimal anchor frame in different training sets. The Backbone contains a focus structure to realise the slicing operation while the Neck uses a new FPN structure to enhance the propagation of low-level features [21]. As a result, YOLOv5 achieves a reduction in computation complexity at least by a factor of four [22]. As compared to the previous versions, it is a lightweight algorithm that trains and infers more quickly while performing positively. For this reason, YOLOv5 has the potential to be the most effective for object detection operations for time-critical applications such as the detection of a person lost in the dense forest. Muhammad etal. [23] reviewed and evaluated the detection algorithms when objects are hidden by occlusions, present in low-light images, or they are merged within the background. Their comparison included Faster-RCNN, Mask R-CNN, YOLOv3, and Cascade Mask R-CNN [24] on publicly available dataset such as ExDark [25], CURE-TSD [26], and RESIDE [27]. These datasets contain images and videos taken under challenging environments such as low-light. In our case study of forest, places under dense tree canopy resemble with darkness. To the best of our knowledge, the object detection algorithms trained on day light images are not tested in the dark. Hence, the purpose of this paper is to evaluate the performance of YOLOv5 to detect a person and various FHI such as deadwood and wildlife signs in the forest areas where light is impenetrable during the day. We tested the algorithm under a range of light variations.

The main contributions include: 1) training YOLOv5 algorithm on a custom dataset containing images of FHI such as deadwood and burrows (wildlife signs) taken during daylight, 2) incorporating an external sensing platform for forest monitoring through a quadruped robot 3) analyse the accuracy of real-time detection against the illumination variance using a chroma meter.

# 2. Methods and Materials

## 2.1. Unmanned Forest Ranger

The purpose of the quadruped machine is to monitor the health of the forest as it navigates through trees and uneven grounds. The Unitree Aliengo robot which has been selected for this study is capable of achieving numerous motions. Thanks to the robot's 12 high-performance servo motors, evolutionary gait motions enable it to walk through a range of terrains and conditions. The servo motors are arranged in places relevant to the robot fuselage, with three servo motors attached in each leg to achieve calf, thigh and hip angular motions. With this configuration in mind, the unmanned vehicle becomes most suitable for forestry environments due to uneven terrain with potential ground obstacles faced during the mission (i.e. logs, twigs, tree roots, rocks etc).

## 2.2. External sensory platform

Although the robot consists of integrated perception sensors, several challenges have been faced during the development process. For instance, controlling the robot essentially relies on quick responsivity and stability. Therefore, incorporating detection algorithms into the same computer that controls the machine will result in the CPU using extensive energy, eventually reducing the performance and introducing constant autonomy delays. Additionally, the visionary sensors currently integrated are only facing forward with a limited field of view. Therefore, developing an external box that can sit on top of the robot to accommodate in sensing the non-viewable areas will certainly enable further autonomy and improved forest monitoring.

The aim of developing such a platform is to detect various objects, tree species, and humans. So far, the system developed has been purely focused on detecting deadwood, tree species, persons, and burrows. Although the detection approach was found successful, numerous challenges have been faced in the forest while walking under trees and gloomy areas, although it was sunny and bright. Hence, developing the sensing box to fit above the robot will carry out detection of these objects under different lightning streams while also taking into consideration the type of camera used.

Initially, an off the shelf enclosure was used to store the hardware which is connected to the camera. The aim is to collect various information from specified objects using AI and machine learning techniques as the robot moves around a forest. Since the robot motions may create distortions to the camera quality as the robot is moving in different terrains, a WG2X Feiyutech gimbal was used to ensure that stability is maintained throughout the tests. Hence, the set-up made incorporates a single-board computer (SBC) Raspberry Pi (RPi) as well as the readily available low-cost RPi camera. On the other hand, a GoPro9 camera will also be used to carry out the same analysis under similar illuminations before the results are compared. Table 1 illustrates the specifications of the selected cameras and their overall costs.

Since the WG2X gimbal is only compatible with GoPro, a SolidWorks geometry was designed and 3D printed, weighing approximately 36 grams to accommodate the SBC camera. It is worth mentioning that the model developed is only used for exploration purposes in this initial phase. Figure 1 illustrates the quadruped robot accommodating the external sensing box. A 73Wh portable battery is used to deliver a long-lasting power to the SBC as it collects data from the forest. Once the data was collected from the RPi camera, the GoPro9 was then easily switched and connected to the same SBC to re-collect and compare the data. With the sensing platform now incorporated into the robot, the responsivity of the real-time detection algorithm through various illuminations was compared between a low-cost and a high-cost camera. Two cameras will be connected to the RPi respectively through a CSI port while the GoPro9 connects through a video capture card. With regard to the internal functionalities, a server will constantly be running on the cloud, which includes the trained machine learning algorithm and the media server. For clarity, the primary function of the media server is to enable Web real-time communication (WebRTC) which is a browser-based technology for video conferencing, file transfer and screen sharing without any external applications or plugins. With this user-friendly interface, the machine learning algorithm uses a Flask server to get images from the media server. The outputs are then sent back to the media server via HTTP Post, and is displayed to the viewer in the form of drawing boxes on each object detected [28, 29]. For our system, the preferred network is 5G. However, in situations where there is no 5G coverage in the area, we

**Table 1**
Comparing GoPro9 specification against a low-cost RPI camera

| Specification | GoPro9 | RPI Camera |
|---|---|---|
| Resolution (Megapixel) | 23.6 | 12.3 |
| Sensor | CMOS | IMX477R |
| Back Focus | Auto | Auto |
| White Balance | Auto | Manual |
| Audio | Yes | No |
| Weight | 450g | 50g |
| Cost | £350 | £50 |

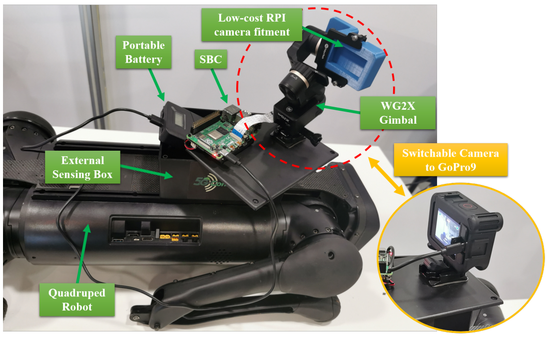


**Figure 1:** Aliengo Quadruped robot accompanied with the external sensing box

use WiFi instead. When both are unstable because of emergency situations such as fire, we designed our system to automatically switch to the edge computer (RPi) instead of the cloud virtual machine (VM). The main difference between the edge and cloud VMs is that the edge uses the lite version of TensorFlow, whereas the cloud uses the full version (TensorFlow 2). This is because our cloud VM is more powerful than the edge computer with limited memory and CPU. We use network RSSI to determine if the streaming and detection should happen locally or remotely. For example, if the RSSI is more than -80dBm (stable), everything happens on the cloud virtual machine (VM). However, if connection is unstable or unavailable, it will automatically switch back to the local device where both the streaming and detection will be performed. This paper assumes that there will always be a 4G/5G or WiFi network in the area where the test is being conducted. If neither network is available in the area, offline detection can be used. The drawback of offline detection is that there will be no real-time data collection, and data will only be accessible after the robot returns to the station.The full architecture of quadruped robot-based object detection is shown in Figure 2.

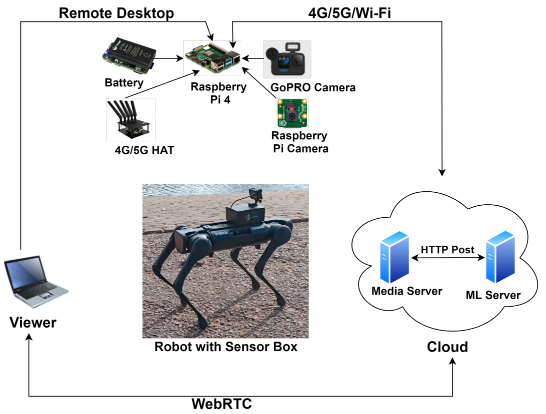


**Figure 2:** System design of the forestry detection system

## 2.3. Dataset and Training

For forest use cases, the custom dataset comprised of 200 images captured using a 4K quality RGB camera with two classes: deadwood and burrow. The images were resized to 640x640 and labelled using Makesense.ai [30]. The images were annotated with all the classes using bounding boxes. The YOLOv5 pre-trained on Common Objects in Context (COCO) [31] dataset containing 800,000 of person instances in images taken during daylight. We used this model for person detection. The model was re-trained on custom datasets for FHI detection. The hardware to train the model included a Lenovo laptop equipped with an NVIDIA Quadro RTX 3000 GPU, 8265U CPU at 1.80 GHz of Intel Core i5, 8 GB of RAM running on a Windows 10 64-bit system. The dataset was divided into train and test data with a ratio of 80:20 where the model took approximately 1 hour and 23 minutes to train in 200 epochs. Detecting the illuminations at different periods was achieved by using an RS-pro Chroma Meter, which can provide an exposure value according to the illumination in the region. While these measurements were taken, the robot carrying the GoPro and RPi camera respectively was used to detect the accuracy of the algorithm based on real-time images taken from the forest.

**Table 2**
Accuracy of YOLOv5 Model on Custom Dataset (Deadwood, Burrow)

| Classes | mAP@0.5 | mAP@0.5:0.95 | Precision | Recall |
|---|---|---|---|---|
| Deadwood | 0.996 | 0.743 | 0.994 | 0.979 |
| Burrow | 0.996 | 0.755 | 1 | 1 |
| All | 0.996 | 0.749 | 0.997 | 0.989 |

# 3. Results and Discussion

Once the model was completely trained, raw pictures and a videos were fed into the model with a confidence threshold of 0.25. This resulted in the algorithm detecting deadwood and burrows with a prediction value of more than 90% in almost all instances. The model improved significantly in terms of precision, recall and mAP after 70 epochs and became stable after 100 epochs, which means stopping the model early would give almost the same results in 50% less time. The mAP results for each class at IoU 0.5, from 0.5 to 0.95, Precision, and Recall are shown in Table 2. The performance of the algorithm was preliminarily tested through the external sensing platform placed on the quadruped robot. Initially, it was observed that the tests took place in a cloudy day in Oakland Park, Birmingham, UK. Figure 3 illustrates the exposure value (EV) which was initially taken at 4pm (GMT) with en EV rating of 586.9. As the sun continued to set, the EV ratings have consistently reduced to approximately 215.5 at sunset, while it reached below 10 at dusk. For the real-time object detection in the forest, the web-based application running on the cloud was utilised [28, 29]. The detection of deadwood, burrows, and person was performed on and after sunset under three EV's, i.e. 100, 20, and 10. The detection accuracy of burrows, deadwood and person using GoPro and RPi cameras are shown in Figure 4, 5, and 6 based on the three respective EV's. In Figure 4, the detection accuracy of all three objects was relatively accurate on both cameras between 2m-6m. However, the accuracy begins to immensely deteriorate at 8m, 10m and 12m for burrows and deadwood using

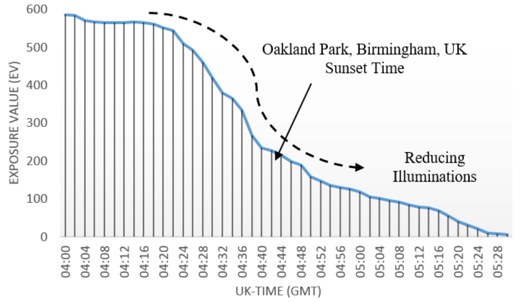


**Figure 3:** Exposure value measured between 4-5:30pm in Oakland Park, Birmingham, UK under a cloudy sky

the RPi camera. On the other hand, the GoPro remains stable with the accuracy consistently maintained above 50% especially for person detection. As for Figure 5, the

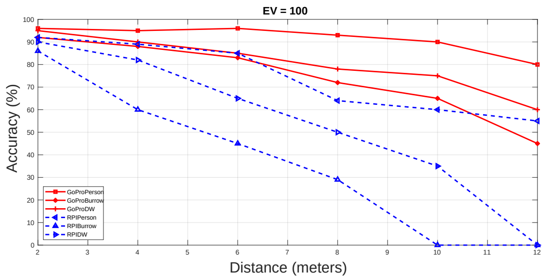


**Figure 4:** Detection accuracy according to distance under 100 EV

detection algorithm can be seen to immensely reduce as the the distance is increased from the object. The GoPro remained stable with accuracy maintained above 75% while the RPi camera was accurate above 35% for person detection, but could not detect burrows at 10m and deadwood at 12m. During the period of 10 EV, Figure 6 shows

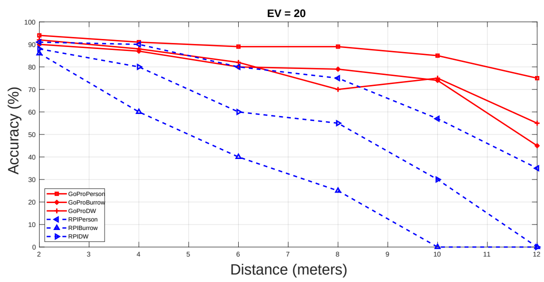


**Figure 5:** Detection accuracy according to distance under 20 EV

how the accuracy of detection became increasingly effected especially at larger distances. In fact, both cameras failed to detect anything at 12 meters. The GoPro showed an improved response of 67%, 60% and 55% for person, deadwood and burrows in comparison to the RPi results of 57%, 30% and 0% at 10m. The Figure 7 consists of GoPro images to show the detection of person at 10 EV and burrows under 20 EV with the accuracy percentage.

Although both cameras have successfully detected objects after sunset to a certain extent, the YOLOv5 is trained on thousands of images under day light which may not be suitable for application that requires detection of distant objects with low light illuminations. The burrows could not be detected with RPi under all three EV's at 10m and 12m, possibly because of their size. Hence, it can be concluded that camera selection plays a major role in detection, but the limitation of detection after sunset will always become a challenge based on the dataset that has been trained for this system.

## 4. Conclusion

In this paper, we proposed and utilised a quadruped robot as a forest ranger to detect persons and various health indicators under low visible conditions. An external sensing platform was developed which includes an SBC that connects to a GoPro and a low-cost RPi camera. This has been performed to estimate the object detection accuracy in dense forests or adverse weather conditions. The object detection was performed by utilising YOLOv5 model in a cloud-based application before and after sunset. Our results show that a person could be detected after sunset at around 10m via both cameras with good accuracy, which will be helpful for search and rescue missions. As for carrying out detection after dusk, some other measures will be required, such as using a thermal camera instead of RGB. To increase the detection accuracy of FHI, we will need to expand our dataset with more images of burrows and deadwood along with other key FHI. We have found some large-scale datasets in the literature containing videos and images captured in a harsh environment. In the future we aim to train YOLOv5 model on these datasets and evaluate its performance.


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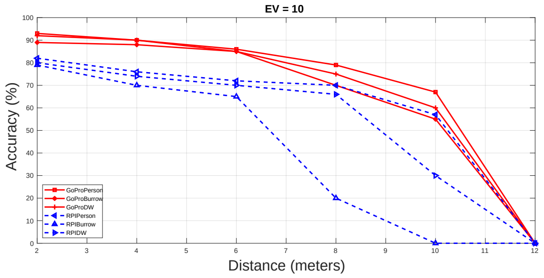


**Figure 6:** Detection accuracy according to distance under 10 EV

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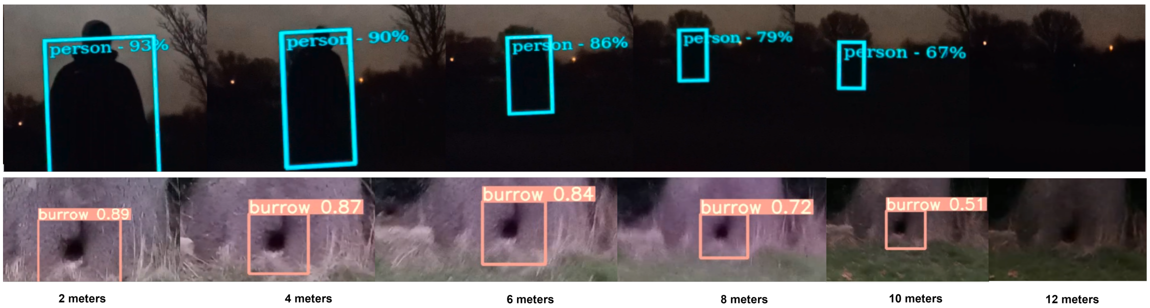


**Figure 7:** Detection of Person on GoPro images under 10 EV and Burrows under 20 EV at various distances

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