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AI-Powered Water Spray Mechanisms for Feline Repellence in Ecological Conservation

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ABSTRACT

The AI-powered feline repellent system using AlphaVision addresses ecological and public health challenges caused by domestic and stray cats. Cats are responsible for the annual loss of millions of birds and disrupting ecosystems, furthermore their faeces can transmit toxoplasmosis, posing risks to unborn babies and immunocompromised individuals. AlphaVision, which is the prototype system developed in this study, integrates Jetson Nano, Raspberry Pi Zero 2 W and MobileNet-SSD v2 model with a water-spray mechanism to deter cats humanely. The system uses real-time AI detection via a trained MobileNet-SSD v2 model to identify cats and activating a water spray upon detection. Field tests showed 82% detection accuracy under optimal conditions (bright lighting, 2-meter range) but reduced accuracy at greater distances, wider angles and low-light conditions. The project emphasizes sustainability by employing energy-efficient hardware and a power-efficient water-spray mechanism. AlphaVision demonstrates the potential of AI-based solutions for wildlife conservation and public health. Future improvements include expanding the dataset, optimizing the model and enhancing hardware to improve performance across diverse real-world scenarios.

Keywords: Feline Repellence, Ecological Conservation, Artificial Intelligence (AI), Water Spray Mechanisms

1. INTRODUCTION

Domestic and stray cats are known to cause substantial disruptions to local ecosystems and public health. In Colombia for example, cats are estimated to kill between three to twelve million birds annually, illustrating their severe ecological impact [1]. Globally, birds play a critical ecological role by regulating insect populations, consuming approximately 400 to 500 million tons of insects each year, which is essential for maintaining biodiversity and healthy garden ecosystems [2]. Beyond ecological issues, cats also pose health risks to humans. Their faeces can harbour toxoplasmosis, a parasitic disease that is especially dangerous to unborn babies and immunocompromised individuals [3]. Other pathogens, such as E. coli, Salmonella, roundworms and hookworms, can also be transmitted through cat waste [4].

Numerous cat deterrent systems have been developed, such as ultrasonic repellents and motion-triggered water sprinklers. Ultrasonic devices emit high-frequency sound waves intended to discomfort animals, yet studies have shown their effectiveness is limited due to environmental interference and animal habituation over time [5][6]. Traditional motion-activated sprinkler

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systems like the Scarecrow are also used to deter cats. However, they often suffer from inefficiencies including water overuse, overspray onto non-target areas and a lack of intelligent targeting [7][8].

Recent research in precision agriculture and AI-based deterrent systems suggests a growing interest in leveraging edge AI technologies for animal repulsion [9][10]. However, very few systems have effectively integrated real-time AI detection with targeted mechanical deterrents to address the problem of feline intrusion. Most conventional systems lack the capacity to intelligently identify animals and adjust deterrent mechanisms based on spatial data.

This paper introduces AlphaVision, an innovative AI-powered feline repellent system that integrates the MobileNet-SSD v2 deep learning model with a directional water-spray mechanism. The system uses the Jetson Nano Developer Kit and Raspberry Pi Zero 2 W to enable real-time cat detection and targeted deterrence. The AI model was trained with a specialized dataset featuring various feline poses, lighting conditions and viewing angles, using transfer learning and data augmentation techniques to enhance detection performance. Key training parameters such as learning rate of 0.001, batch size of 16 and 50 training epochs were applied using the Adam optimizer to ensure model convergence [11][12].

Unlike conventional sprinklers that indiscriminately spray water, AlphaVision's servo motor directs the nozzle based on the detected cat's location, derived from the bounding box centroid provided by the AI inference. This enables focused spraying within a 180-degree arc, significantly reducing water usage and enhancing deterrence precision. The system's modular design and energy-efficient operation make it suitable for sustainable urban deployment [13][14].

In summary, this paper contributes to the development of an eco-friendly, AI-based, intelligent feline repellent that surpasses existing systems in precision, adaptability and sustainability. The proposed solution addresses current limitations in the literature and presents a comprehensive evaluation of system performance under various environmental and operational conditions [15].

2. MATERIAL AND METHODS

Figure 1 illustrates the core components of the system, emphasizing the Jetson Nano Developer Kit as the AI processing hub. The Jetson Nano processes the video feed from a connected webcam, analysing it in real-time using the MobileNet-V2 deep learning model trained for cat detection. The Jetson Nano operates independently of the primary power grid, ensuring adaptability and portability. Upon detecting a cat, the Jetson Nano sends a signal to the Raspberry Pi Zero 2 W, which acts as the control unit for the system. The wireless communication between the Jetson Nano and Raspberry Pi Zero 2 W enhances the flexibility of the system, allowing the components to be placed independently without physical connections. It then processes the signal to activate the water spray mechanism. Powered by a lithium-ion battery pack, the Raspberry Pi Zero 2 W also supplies power to the 5V relay that controls the 12V water pump.

The Raspberry Pi Zero 2 W additionally manages the servo motor, which adjusts the direction of the water spray. The water pump, activated by the relay, pumps water to the nozzle, while the servo motor, capable of rotating up to 180 degrees, ensures that the nozzle can cover a wide area. This setup enables accurate targeting of the detected cat, maximizing the system's effectiveness in deterring feline intrusions. The system's power supply design prioritizes reliability and efficiency. The Jetson Nano and its webcam are powered by a separate portable power source, ensuring stable operation. The Raspberry Pi Zero 2 W, along with the water pump and servo motor, relies on a lithium-ion battery pack paired with an LM2596 DC step-down converter, which reduces the 15V battery output to 5V for the Raspberry Pi. This design ensures consistent power delivery to all components, accommodating the high energy demands of the water pump and servo motor. The servo motor's direction is computed based on the bounding box centroid of the detected cat. The AI model's inference provides positional data (e.g., x-y centre of detected object), which is mapped to an angular range (0° to 180°) using PWM signals generated from the Raspberry Pi.

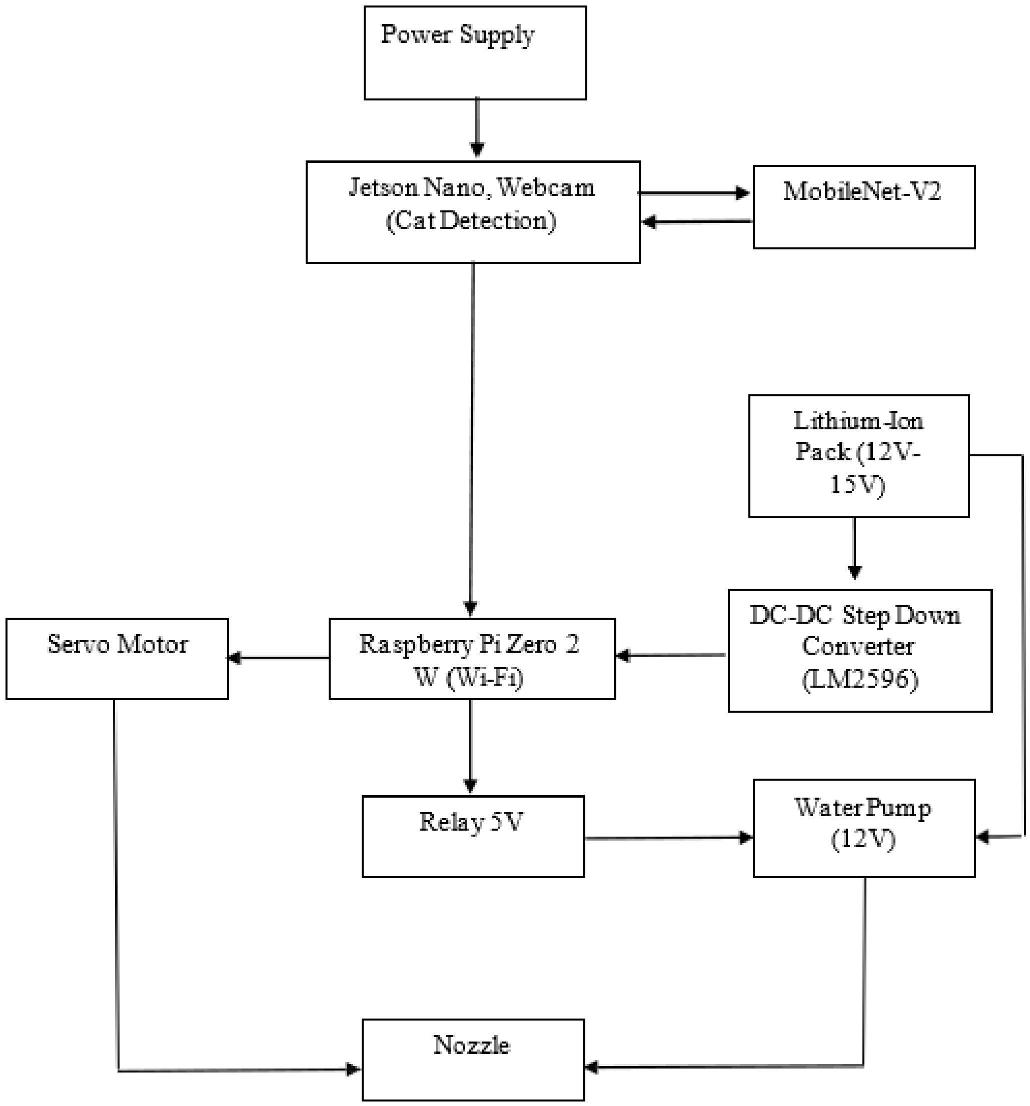

Figure 1. System block diagram

2.1 Circuit Design

The most innovative aspect of this project lies in its circuit design. The objective of the circuit design process is to ensure the functionality, accuracy and precision of the electronic system, minimizing errors during implementation. Circuit design involves constructing and deciding the physical layout of an electronic circuit. For this project, the schematic circuit diagram was designed using Fritzing, a user-friendly software for creating electronic circuit layouts. The circuit integrates a Raspberry Pi, servo motor, water pump, relay module and power supply components.

The Raspberry Pi acts as the main controller, processing input signals and controlling output devices. The schematic circuit diagram is illustrated in Figure 2, showcasing the integration of the servo motor, which controls directional spraying, and the water pump, which activates when a cat is detected. The power supply ensures stable voltage for the operation of all components, while the relay module provides the necessary switching mechanism for the water pump.

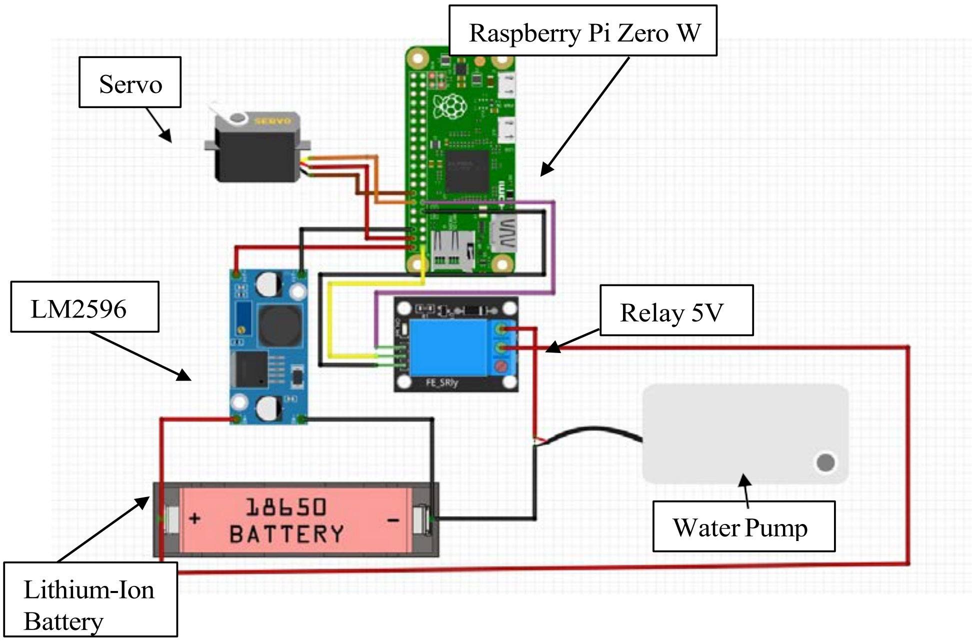

Figure 2. Schematic circuit diagram

2.2 Prototype CAD Design

The prototype design for AlphaVision hardware as shown in Figure 3 was created using FreeCAD, with dimensions in millimetres. The design features a clamp to secure the servo and nozzle, ensuring stability and allowing adjustments for troubleshooting. An adjustable holder enhances alignment precision and troubleshooting efficiency. The 3-liter water tank includes a 6.35mm hole for connecting a tube to the water pump, enabling efficient water flow to the nozzle. The modular and adjustable design supports easy maintenance, flexibility and system longevity. Following the finalized CAD drawings during assembly will minimizes errors and ensures precision in integrating components like the servo, nozzle and water tank.

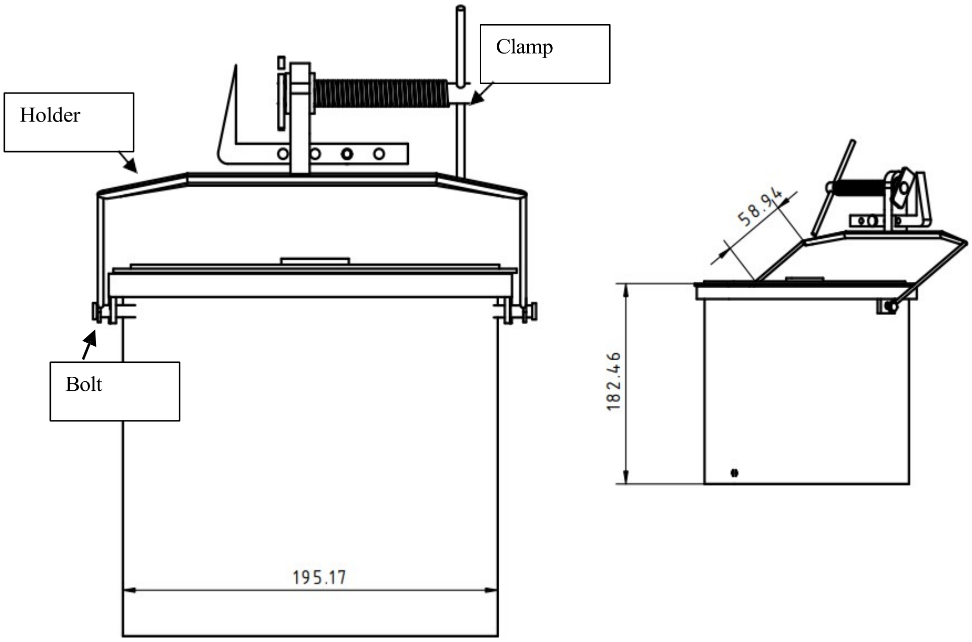

Figure 3. Prototype design using FreeCAD (dimensions in mm)

2.3 Model and Dataset Details

The MobileNet-SSD v2 model used in AlphaVision was trained using a custom dataset comprising images of cats captured in varied lighting conditions, poses and angles. Data augmentation techniques such as rotation, flipping, and contrast adjustment were applied to improve generalization.

Training was conducted using the PyTorch framework. Key parameters included:
- Epochs: 50
- Learning Rate: 0.001
- Batch Size: 16
- Optimizer: Adam
- Loss Function: Smooth L1 Loss for bounding box regression and Cross-Entropy for classification

The dataset was annotated using LabelImg, and bounding boxes were generated for each image. A transfer learning approach was applied, initializing the model with pre-trained weights from the COCO dataset, then fine-tuning on cat-specific data.

Approximately, 800 labelled images were used in total, divided across different times of day and views (front, back, side). Each session captured 80–100 image frames. The model's performance was validated using a 20% validation split, with detection accuracy evaluated under different environmental conditions.

3. RESULTS AND DISCUSSION

3.1 Training

The MobileNet-SSD v2 model was trained for 50 epochs using a dataset of approximately 800 annotated images. Data augmentation was used to enhance variability. Figure 4 presents the training loss curve divided into three learning phases:

3.1.1 Initial Phase

At the beginning of training, the loss started at a high value of approximately 3.5, indicating significant errors in the model's predictions. This high initial loss is expected, as the model is newly initialized and has not yet learned to detect the target objects accurately. During this phase, the model begins its learning process by adjusting its parameters to identify patterns in the training data. The steep reduction in loss during the early epochs reflects the model's rapid adaptation to basic features, such as object edges and outlines, which form the foundation for more complex feature learning in later stages.

3.1.2 Middle Phase

As training progressed, the loss decreased rapidly and then began to fluctuate around 1.0. These fluctuations indicate that the model was learning to recognize more complex features of the objects, such as variations in shape, size, texture and lighting conditions. This phase is critical, as the model moves beyond basic pattern recognition to identifying nuanced details that improve object detection accuracy. However, the observed fluctuations suggest that the learning process was not entirely smooth. External factors, such as insufficient data diversity or overly large learning rates, may have caused this instability, highlighting areas for potential optimization.

3.1.3 Final Phase

Toward the later epochs, the loss curve stabilized below 1.0, signalling that the model achieved convergence. At this stage, the model had sufficiently learned to predict object classes and their bounding boxes with reduced error. The stabilization indicates that the model had fine-tuned its parameters to minimize discrepancies between predictions and ground truth labels. This phase marks the point where the model has achieved a balance between learning and overfitting, as it effectively captures the key features of the objects within the training dataset.

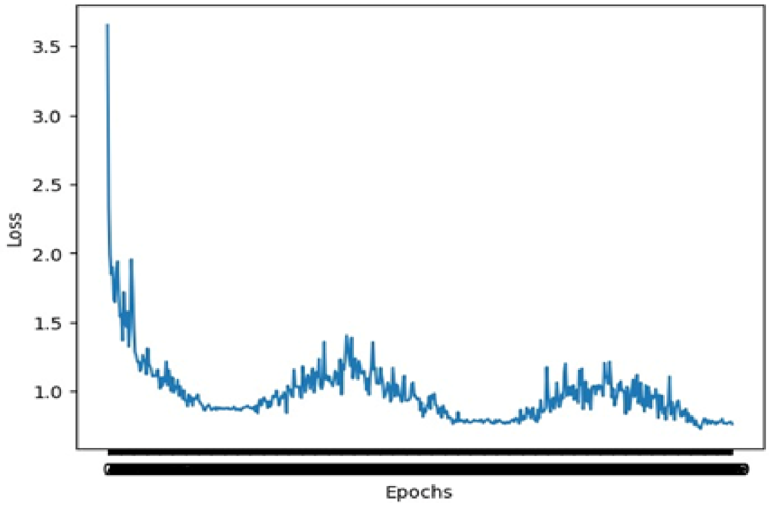

Figure 4. Training results

3.2 Model Accuracy

To evaluate the effectiveness of the model, tests were conducted towards data collected during two distinct time periods: 2 p.m. to 3 p.m. (daylight) and 7 p.m. to 8 p.m. (low light). These sessions were conducted to analyse the performance of the AI model under varying lighting conditions. Four image capture sessions were conducted per time period, and each session consisted of approximately 80–100 image frames. Images featured cats of varying sizes, fur colours and physical traits, including one with a missing ear, to test the model's robustness.

The dataset included various feline poses such as relaxing, sitting, grooming and walking. It also captured cats from different angles, specifically front and back views. Side-view images were not available due to camera placement and will be added in future dataset expansions to improve model generalization. Table 1 summarizes the detection accuracy of the model based on the time periods and cat orientations, respectively, while Figure 5 and 6 visualize the results in graph for better illustration.

Table 1 Detection accuracy based on different time periods and cat orientations

Time Period	Front View of Cat	Back View of Cat
2 p.m. to 3 p.m.	98 %	96.6 %
	91 %	73.8 %
	98 %	71.6 %
	97.9 %	74.9 %
7 p.m. to 8 p.m.	96.6 %	69.2 %
	96.7 %	67 %
	84.2 %	63 %
	88 %	63 %

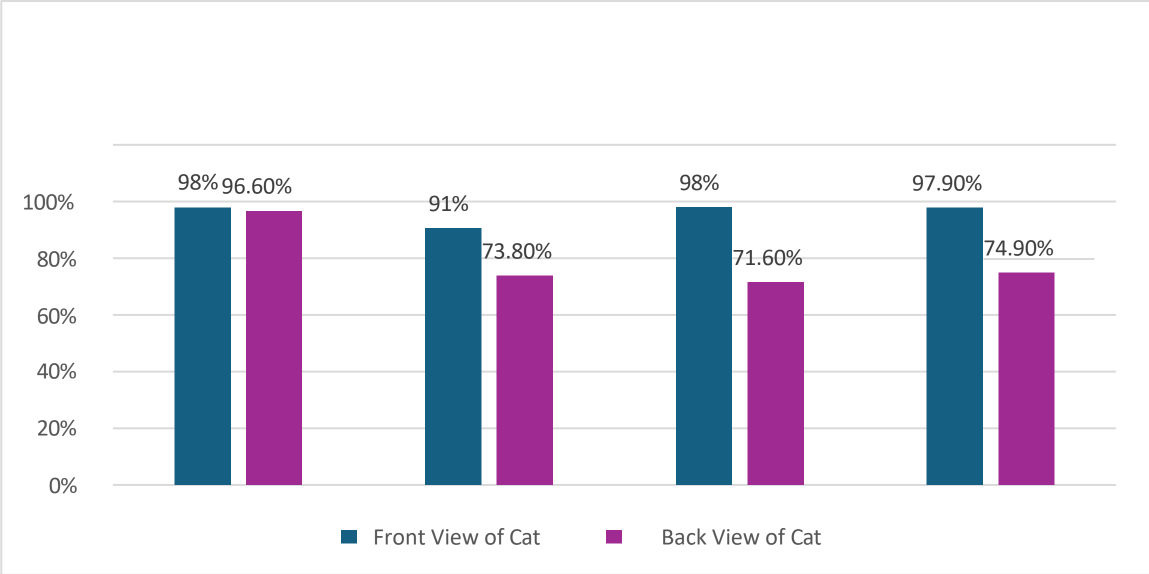

Figure 5. Results of cat detection for data collected between 2p.m. to 3 p.m.

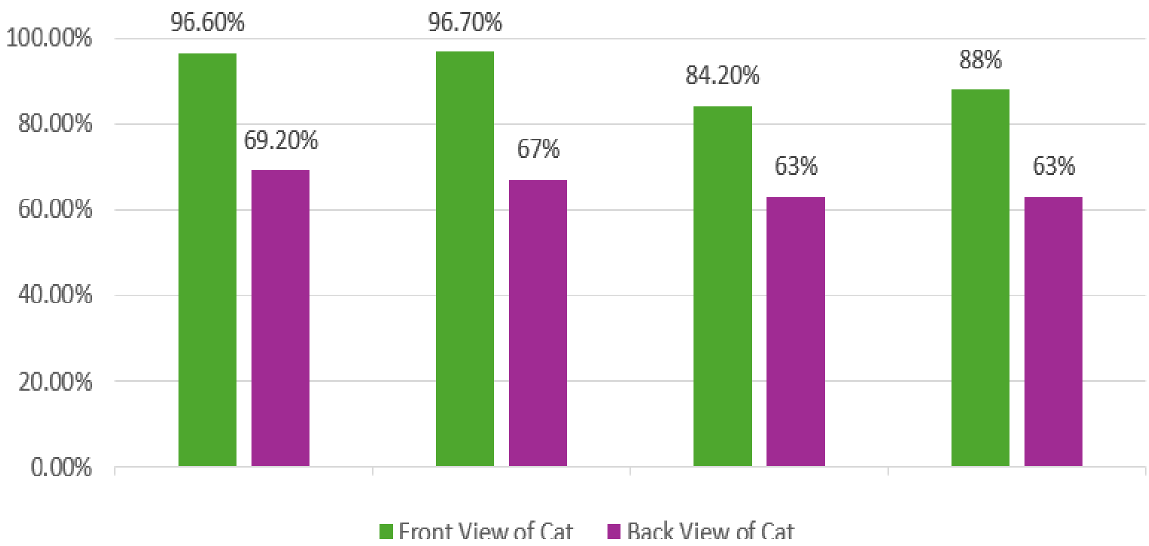

Figure 6. Results of cat detection for data collected between 7 p.m. to 8 p.m.

These accuracy percentages indicate that the model performs best under bright lighting and with the front view of the cat. Detection from the back is less reliable, especially in dim lighting conditions. This is likely due to fewer distinguishing features being visible from the back, as well as the shadowing effects under low light.

Figure 7 visualizes the detection results by different poses and angles. The reason for these differences is to improve reliability through varying cat types and behaviours in similar lighting.

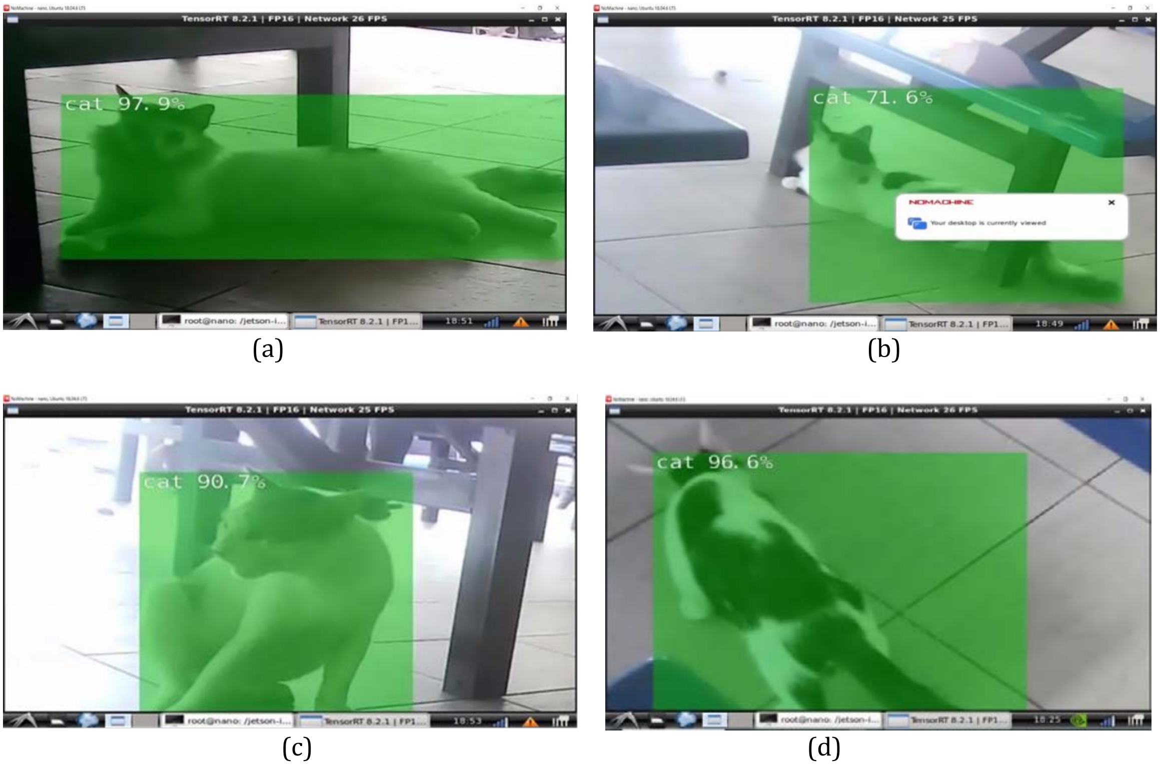

Figure 7. Detection results in various cat poses: (a) Relaxing – front, (b) sitting – back, (c) grooming – front, (d) walking – back

3.3 Hardware Setup (AlphaVision)

The AlphaVision prototype, shown in Figure 8, was developed based on the finalized CAD design. This version was physically constructed and deployed for testing. It integrates all hardware components: Jetson Nano (inference engine), Raspberry Pi Zero 2 W (controller), 12V water pump, relay and servo motor for directing the nozzle.

Once a cat is detected, the system activates the water spray mechanism within 1 second. The servo's angular direction is computed using the x-coordinate of the detection bounding box, which is mapped to a PWM signal for 0°–180° rotation. This allows targeted deterrence rather than random spraying. The full setup is hidden in a flowerpot with artificial plants, offering both aesthetics and functionality.

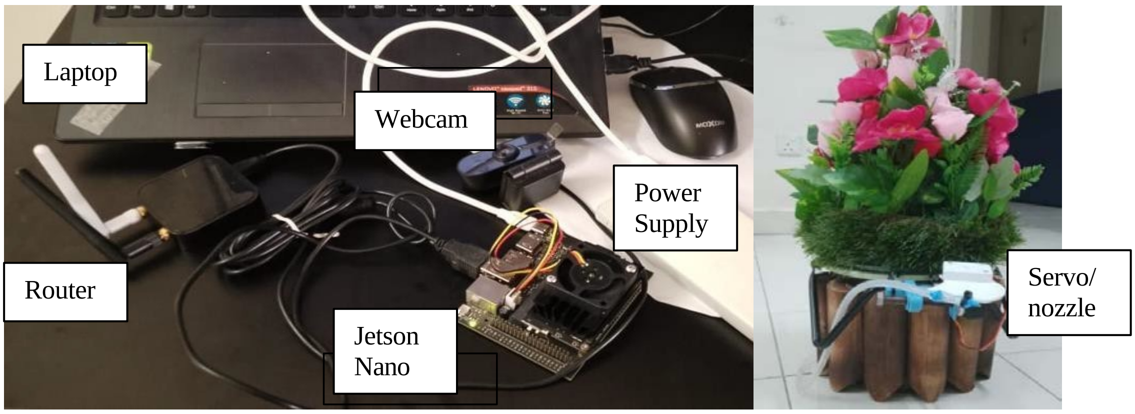

Figure 8. AlphaVision hardware setup

3.4 AlphaVision System Accuracy vs. Model Accuracy by Distance and Angle

Analyses were conducted to evaluate the detection performance at distances of 1 meter and 2 meters and angles of 0°, 45°, and 90°. These tests were performed to assess how positional changes influence detection accuracy. Both AlphaVision system, which includes the full system response such as detection, servo rotation and water-spray activation is tested against the trained MobileNet-SSD model to see the overall performance. Table 2 and Figure 9 summarize the results.

Table 2 AlphaVision and model detection accuracy by distance and viewing angle

Distance (m)	Angle (°)	AlphaVision Accuracy (%)	Model Accuracy (%)
1	0	99.9	100
1	45	100	100
1	90	98.4	60.7
2	0	94	98.5
2	45	90	98
2	90	85	59

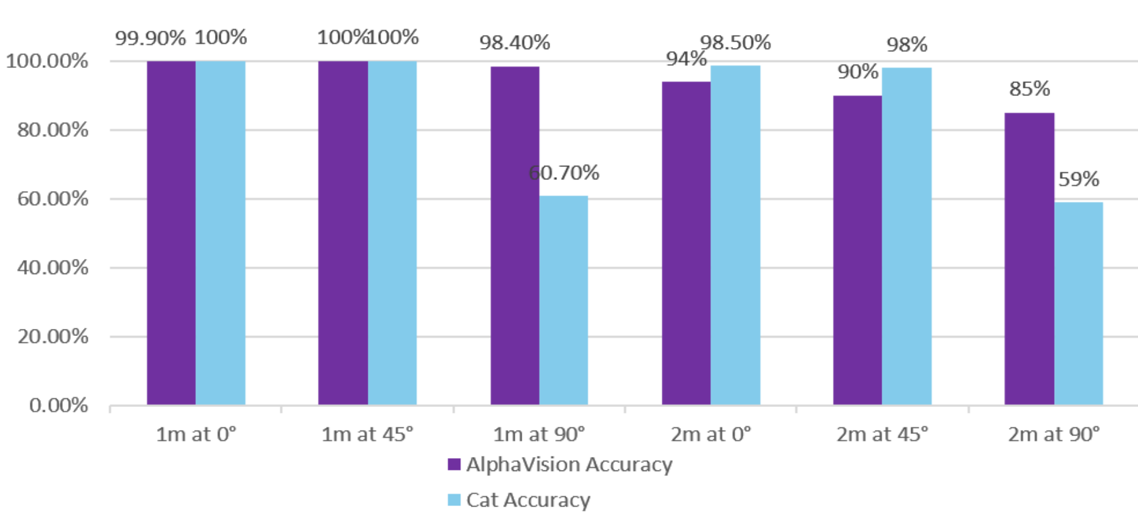

Figure 9. AlphaVision and model (cat) accuracy (%) vs. distance (m) and angle (°)

At 1 meter, AlphaVision achieves excellent results across all angles. At 2 meters, performance drops slightly, particularly at 90°, where detection becomes more difficult due to the limited visibility of key feline features. This performance difference highlights the integrated system's sensitivity to real-world conditions like mechanical lag and bounding box estimation at farther distances. Improvement could be made by enhancing resolution or introducing dual-angle camera inputs.

4. CONCLUSION

The AlphaVision project has successfully developed utilising an AI-powered feline repellent device that integrates a camera detection system with a water-spray mechanism for precise and humane cat deterrence. The device was designed using FreeCAD, considering key factors such as effective range, detection angles and environmental adaptability. The schematic circuit, created in Fritzing, ensured seamless integration of hardware components, including the servo motor and water pump. These components provide accurate targeting and efficient water-spray action, making them essential for repelling cats without causing harm. The AI system, powered by the MobileNet v2 model, achieved an impressive accuracy rate in detecting feline presence. The training loss stabilized below 1.0, confirming the model's convergence and its ability to generalize well under various conditions. Field performance tests further demonstrated the device's effectiveness, achieving significant reductions in feline activity in protected areas. Key performance data highlighted accuracy rates of 98% and 96.6% for front and back views, respectively, under normal lighting conditions.

Future work will focus on addressing other parameters such as distances greater than 2 meters, different cat poses like the side views, cats with physical disabilities as well as uncommon poses, together with low-light conditions such as at night time. These will increase the robustness of the system.

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