Applying Artificial Intelligence, Machine Learning, and Prompt Engineering for Image Recognition of Burmese Pythons

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Abstract: - Google's Teachable Machine, Meta's Segment Anything Model, and the Python programming language are utilized to develop a machine-learning model for identifying Burmese pythons and alligators in natural settings in the Everglades using image recognition. Aimed at enhancing wildlife conservation efforts, the model was trained using over 1000 image samples. It demonstrates potential for automated wildlife monitoring, with promising initial results in species identification, classification, and geographic distribution, especially for invasive species like the Burmese Python in extensive remote wetlands like the Everglades. Prompt engineering lets us reuse powerful models for wildlife detection without retraining, which makes AI faster and easier to use. This approach underscores the value of accessible Artificial Intelligence tools in environmental management and species protection.

Key-Words: - prompt engineering, artificial intelligence, machine learning, wildlife conservation

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1 Introduction

Burmese Pythons are an invasive species in the Everglades and have become a complex ecological challenge by rapidly evolving into an apex predator. It has started causing significant ecological imbalances in the Everglades, as there are no natural predators to control its population. Efforts to track and measures to control its spread have so far had limited success. Artificial Intelligence (AI) and Machine Learning (ML)are at the forefront of technological advancements that offer new methodologies for tracking this invasive species. This study aims to explore artificial intelligence and machine learning techniques to devise more effective methods for monitoring the Python population. If successful, these techniques have great potential to transform the tracking of invasive species in the field of wildlife management and provide a crucial edge in the fight to preserve biodiversity and the ecological integrity of wildlife ecosystems. Recent studies have highlighted the dramatic impact of the Burmese python, an invasive predator, on native wildlife in the Florida Everglades. Studies such as [17] demonstrated that deep learning on large camera trap datasets can yield species recognition accuracies as high as 96.6%. This research follows an increasing trend in using prompt engineering to adapt powerful AI models such as CLIP or vision-language transformers for environmental studies without needing a lot of retraining. Other works, including [12] and [13], have shown that prompt engineering can dramatically enhance visual and multimodal model performance without retraining. This body of research provides a foundation for applying AI to monitor invasive species like the Burmese python. The python's presence has led to notable declines in native species such as rabbits, foxes, possums, and more. The situation worsens as these pythons extend their territory, showing the need for urgent and effective intervention. Traditional methods to combat this issue, such as deploying human hunters, have yielded little success. They're not just resource-intensive but also lack scalability. Even though pythons are large snakes, their coloring and behavior allow them to blend into the environment. Since they are so hard to find in the wild, estimating the number of pythons is very difficult [4, 5]. This study helps resolve this issue, offering a solution through artificial intelligence, machine learning, and neural networking. Our approach builds upon [11], who used a TensorFlow-based image recognition system integrated with Meta's Segment Anything for accurate python and alligator classification in natural environments and supported the idea that prompt engineering improves performance without retraining.. In addition, techniques such as spatial prompts and optimized visual-language prompting inform the architecture of our system [15, 16]. Our AI model utilizes image recognition, prompt engineering, and neural networking to detect Burmese pythons in their natural environment. It represents a significant shift from human-centric efforts to a more automated, efficient approach.

2 Related Works

Table 1 shows a detailed overview of the frameworks the other authors developed

Reference	Dataset Utilized	Results	Summary
Proposed Method	~1,300 training + test images	Accuracy = 81%, python and alligator classification = 100%	Used a TensorFlow model with Python scripts and image segmentation from Meta's Segment Anything. High accuracy for identifying Burmese pythons and alligators in natural environments.
Chen et al. (2025) [11]	LLM models	Prompt engineering improves performance immensely without retraining.	Reviewed Chain-of-Thought, self-consistency, and CoT prompting. Shows that prompt design replaces ML retraining.
Gu et al. (2023) [12]	Multimodal datasets (with text and image)	High zero-shot performance without fine- tuning.	Comprehensive review of prompt strategies on VLMs (Vision-Language Models). Shows generalized results, not specific to species.
Sahoo et al. (2024) [13]	Text + code benchmarks	Prompt engineering can yield similar or better results than retraining an LLM, but with lower computational costs.	Showed that prompts that are engineered adapt large models to more domains; visual ecology was not tested.
Wang et al. (2023) [14]	Vision foundation models (such as VIT, Flamingo)	Prompt engineering helped model improve at recognizing images even when shown only a few training examples.	Introduced spatial prompts in image models. It inspired the visual segmentation (e.g., Segment Anything) used in our work.
CLIP + Prompt Tuning (2024) [15]	Labeled wild animal photo dataset	Optimizing and engineering CLIP prompts for animal ID increased species classification accuracy.	Used prompt tuning over CLIP to detect wildlife. It is closely related to our study in guiding models without retraining.
Lee & Palmer (2025) [16]	Prompt design experiments	Engineered and structured prompts improved learner outputs.	Supported the need for well-crafted prompts in image input training.
Norouzzadeh et al. (2018) [17]	3.2 million camera trap images	96.6% accuracy in species recognition	Demonstrated the potential of combining deep learning with prompt engineering.
CLAP Bioacoustics (2025) [18]	Animal call datasets	Prompt engineering can yield similar or better results than models that were custom-trained using labeled data.	Demonstrated that prompt engineering alone lets pre-trained models generalize to new audio tasks, including species detection and foreground/background separation, without retraining.

The framework for this study, as shown in Table 1 above, uses prompt engineering to improve image recognition accuracy without retraining large models. By combining Google's Teachable Machine for neural network training, Meta's Segment Anything for pre-segmentation, and Python utilities for efficiency and automation, this study demonstrates how engineered inputs (visual prompts) can enhance model accuracy without retraining. While Table 1 focuses on recent studies in prompt engineering and AI models, other sources were incredibly helpful in this framework. Documentation from TensorFlow [2] and Teachable Machine [1] teaches how to build, train, and export the model for testing and usage. References from the National Park Service [4, 5], USGS [7], and UCF [8] were helpful in setting the study in real-world environmental challenges. Other studies, like [3] and [10], showed that prompt-based methods can work in different places and for different types of animals.

3 Methodology

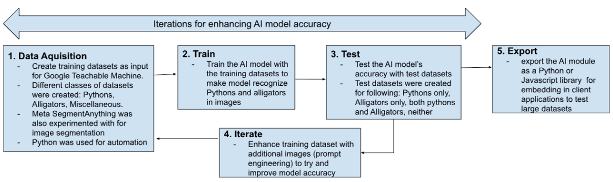

Figure 1: Methodology used in this study shown in a flowchart detailing the steps taken for engineering, training, and testing.

To build the proposed model for species detection and classification, I used many materials such as open-source machine learning platforms, image segmentation tools, and custom Python scripts. These tools were selected for their accessibility, scalability, and ability to be used in prompt engineering; together, they allowed for development, testing, and redevelopment of the model.

3.1 Google's Teachable Machine

Teachable Machine [1] is an AI tool developed by Google designed to make machine learning accessible to a broader audience, allowing users to create simple AI models without much programming knowledge. Teachable Machine emphasizes ease of use and interactivity, enabling individuals to experiment with and learn about AI and ML intuitively.

3.1.1 Teachable Machine Categories

Teachable Machine helps to create and train machine learning models for 3 types of objects: Image, Audio, and Pose classification.
Image Classification lets users classify images into different categories,
Audio Classification lets users recognize sounds or spoken words, and
Pose Classification lets users detect and classify physical poses using a computer's webcam.

Teachable Machine allows for real-time training and testing of models directly in the browser, providing immediate feedback on how well the model is performing.
Once trained, models can be exported to websites, apps, or other studies. They can be downloaded in various formats compatible with TensorFlow for further finetuning, or shared via a link for web applications.
Teachable Machine showcases how AI can learn from data to make decisions or predictions, helping to demystify AI and Machine Learning

3.1.2 Use Cases of Teachable Machine

Education: It is a great tool for teaching the basics of machine learning.
Prototyping: Quickly prototype AI models for creative projects or basic applications.
Experimentation: Allows individuals to experiment with AI easily.

For this study, the default Tensorflow configurations provided by TeachableMachine were used. (50 Epochs, 16 Batch Size, 0.001 LR)

3.2 Meta's Segment Anything Model

Meta's Segment Anything Model (SAM) is an AI model that uses image segmentation to cut out parts in an image or video.

3.2.1 Benefits of Image Segmentation for Teachable Machine Training

Focus on Relevant Features: Segmentation helps isolate the specific features or objects of interest (like Burmese pythons) from the background. This can make it easier for the model to learn what exactly it should be looking for in an image.

Reduce Background Noise: By segmenting the images, you reduce the background noise and unrelated features that might confuse the model during training.

Improve Model Accuracy: With a clearer focus on the target objects, the trained model might achieve higher accuracy and better generalization when classifying new images.

3.3 Python Programming Language

Python is a high-level, interpreted programming language known for its simplicity and readability. Python's simple syntax and readability make it an excellent choice for beginners. The simplicity and efficiency of Python allow for quick development and testing of AI models, which is essential for iterative processes like machine learning and is a very useful tool for rapid prototyping for research and educational studies.

3.3.1 Use Cases of Python in this Study

Use cases include downloading images programmatically using links in image datasets from sites like Wikimedia, GBIF (Global Biodiversity Information Facility)
Renaming images downloaded from various datasets with specific naming conventions so that they can be properly classified and identified for type, source, etc.

These Python utilities have been uploaded to our online repository on the GitHub website, so they can be used by the global developer community at https://github.com/rishi-the-iyer/python-utilities.

3.4 Other Materials

Many supporting platforms and tools were used for handling data, coding, and storing models.

3.4.1 GitHub Online Repository

Utilized to save Python utilities and the Tensorflow Python program for Developer community use and our future reference.

3.4.2 Google TensorFlow AI/ML Framework

TensorFlow is an ML platform created by Google. It builds and deploys machine learning models efficiently. Teachable Machine exports models in a format that is usable with TensorFlow, which allows further development and deployment in different environments.

3.4.3 Google Drive

For storing training datasets, test datasets, and results.

4 Results

The final model achieved 81% accuracy. Burmese pythons and alligators were correctly classified 100% of the time, with the partial errors being in the combination images and miscellaneous categories. Table 2 shows how increasing image samples directly increases model accuracy. Without retraining the model and simply changing the prompt (images for each prototype), the accuracy improved significantly. Accuracy jumped from 69% to 81% as more samples were added

The final model overall showed great accuracy in recognizing Burmese pythons from other species in the Everglades. The interface also displays messages meant for the user's consumption, such as localized error reports and progress information.

The Teachable Machine Project used 4 datasets for testing:
Pythons - 15 images
Alligator - 10 images
Miscellaneous Everglades - 11 images
Combination of Python and Alligator - 7 images

Table 2: Illustrates the increasing model accuracy as the number of sample images used for prompt engineering increases

Model #	Pythons	Alligat-ors	Misc (no pythons or alligators)	Accur-acy
Model 1	445 images	21 images	82 images	69%
Model 2	445 images	529 images	82 images	74%
Model 3	604 images	529 images	82 images	74%
Model 4	605 images	529 images	82 images	79%
Model 5	662 images	594 images	82 images	81%

Comments on Table 2: For model 2, we added alligator images for enhanced accuracy. For Model 4, we moved the alligator image that was failing from test to training set, which also improved the accuracy of other alligator images.

Figure 2: Test image that the final model identified correctly as a Burmese Python.

Figure 3: Test image that the final model identified incorrectly as miscellaneous (not a python or an alligator).

Overall Accuracy: The model achieved an overall accuracy rate of 81%, and an accuracy rate of 100% when identifying Burmese pythons and alligators.

Performance in Mixed Settings: The model exhibited challenges in images that contained both Burmese pythons and other animals. This was particularly evident in densely vegetated areas where multiple species coexist, leading to a lower accuracy in such mixed settings.

Geographic Distribution Analysis: Results show the model's capability in aiding the geographic distribution analysis of these species, particularly for the Burmese python in the Everglades. This holds significant potential for ecological studies and conservation efforts.

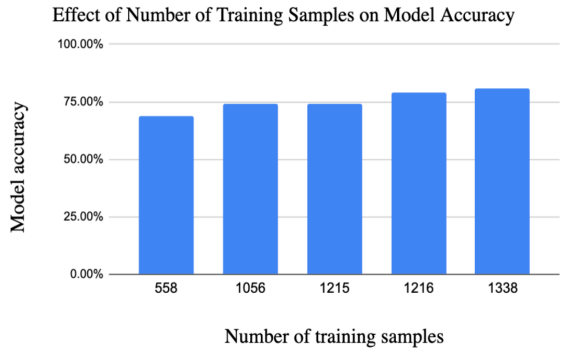

Figure 4: Shows the effect of the number of training samples in prompt engineering on the model's accuracy.

5 Discussion

Future enhancements, especially in complex imaging situations, could see this model's integration with advanced systems like drone-mounted NIR cameras, offering a promising tool for ecological management and invasive species control.

This study's next steps include:
Model Optimization: Enhance accuracy with image segmentation tools for more precise image annotation. Experiment with advanced ML tools like Tensorflow or pyTorch for more accurate and efficient modeling.

Integration with NIR Technology: Explore integration of the model with Near-InfraRed (NIR) technology on drone cameras for real-time monitoring and tracking in the Everglades. "…by using NIR cameras, pythons could be detected 20 percent farther away…" [8]

Field Testing: Conduct field tests in the Everglades to assess the practical effectiveness of the model in a real-world setting.

Scalability and Broader Application: Assess the scalability of the model for other ecological applications and explore its adaptability for monitoring different species or environments, for example, invasive carnivorous tree frogs in Florida.

Prompt engineering is quickly becoming a great alternative to building and retraining new machine learning models from scratch. Instead of developing custom architectures or gathering massive labeled datasets, researchers can now guide large pre-trained models to perform new tasks simply by designing better prompts [11]. This approach uses the capabilities of models like

CLIP, GPT-4, and vision-language transformers, allowing them to adapt with little to no additional training [12]. Studies have shown that prompt-based techniques, including zero-shot and few-shot learning, can have similar or even better results compared to retraining [13]. In fields such as species recognition, engineered inputs have been used to boost classification performance, as demonstrated in wildlife detection tasks [14, 17]. These developments are changing the focus of machine learning development from model training to prompt designing.

6 Conclusion

In this study, we successfully combined methods of prompt engineering, Google's Teachable Machine, Meta's Segment-Anything, and Python to create an AI model for identifying Burmese pythons in images, achieving 100% accuracy in identifying Burmese pythons and alligators, and an 81% overall accuracy. The model excelled in the Teachable Machine's online environment and its TensorFlow implementation in Python. This study shows how reengineering prompts can yield consistently improved results, regardless of retraining the model. Challenges included the model's accuracy in discerning pythons in mixed-species images with lush vegetation, highlighting the need for enhanced segmentation using tools like Meta's Segment-Anything. Overall, our study underscores the efficacy of Artificial Intelligence, prompt engineering, and Neural Networking in addressing environmental concerns such as the invasive species in the Everglades.

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