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Satelite Imagery Detection Neural Network Through Generative A.I

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Introduction

Machine learning through neural networks forms a foundational pillar of modern artificial intelligence. These models simulate aspects of human cognition by learning patterns from data and adjusting internal weights through iterative training. This process enables neural networks to make decisions or predictions based on new inputs, effectively producing consistent and intelligent outputs.

A powerful application of neural networks is in visual sorting systems, where trained models can rapidly classify images based on features such as color, shape, or spatial arrangement such as in satellite imagery detection.

The rise of Generative AI tools, such as the LLM ChatGPT, has introduced new possibilities for enhancing everyday coding projects. Developers now use AI to generate boilerplate code, suggest function improvements, automate documentation, and even simulate user interaction for interface testing. By integrating these tools, projects can be accelerated and enhanced with intelligent feedback loops and creative capabilities.

Prompt Engineering

Prompt engineering is the process of crafting structured inputs that guide AI systems toward more accurate/relevant outputs.

In this project, prompt engineering played a key role in the design and evaluation used throughout model development. We specifically implemented a technique known as Tree of Thought (ToT) prompting, which involves breaking complex decisions into smaller, interpretable branches. .

By prompting through branching logic, rather than single-shot queries, we were able to maintain clarity in decision-making while securing repeatable, high-quality outputs from the AI models used during dataset processing and scripting.

Methodology

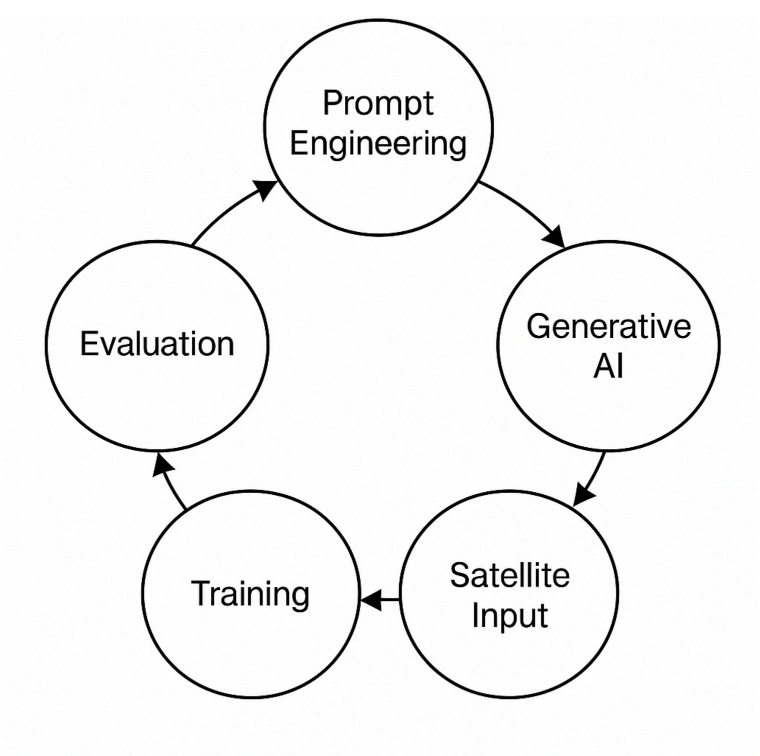
This project aimed to develop a satellite imagery analysis network guided by generative AI, not only to automate classification tasks but also to evaluate the effectiveness of AI-assisted development itself. Using prompt-based design and code generation tools, we trained both a custom convolutional neural network (CNN) and a fine-tuned MobileNetV2 model to classify open fields suitable for emergency landings. Throughout the process, generative AI was used to write, refine, and debug code, allowing us to measure how accurately and efficiently these tools could contribute to real-world machine learning workflows.

Results

This research demonstrates how Generative AI can be integrated into the development of convolutional neural networks (CNNs) to streamline and optimize image classification tasks. By combining AI-assisted code generation with satellite imagery analysis, we created a reliable system for identifying open fields suitable for emergency landings. The resulting network can be adapted for military and civil aviation, offering support in locating safe landing zones in both rural and urban environments. This AI-driven approach enhances response efficiency, planning, and safety in high-stakes aerial operations.

Results

Methedology



Our methology allowed us to properly design Neural Networks which could train and sort through data

Simple Convoluted Neural Nework

Accuracy: 20%

Strengths:
- Custom-built architecture tailored to the dataset
- Easy to modify and interpret
- Low resource usage during training

Limitations:
- Lacked depth and generalization
- Struggled with complex spatial features in satellite imagery
- Underperformed on both classes despite balanced training

MobileNetV2 (Base)

Accuracy: 5%

Strengths:
- Efficient and lightweight pretrained model
- Strong on general image classification tasks (e.g., ImageNet)
- Fast inference

Limitations:
- Significant domain mismatch with satellite imagery
- Features trained on everyday objects didn't transfer well
- Nearly random performance on test data

Fine-Tuned Mobile NetV2

Accuracy: 57%

Strengths:
- Top layers fine-tuned on domain-specific data
- Successfully adapted general features to satellite context
- Achieved substantial improvement in accuracy

Limitations:
- Still undertrained due to limited dataset size
- Some overfitting observed on training samples
- Misclassifications occurred in visually ambiguous regions

Conclusion

This project successfully demonstrated how prompt engineering and generative AI can be leveraged to build, refine, and enhance convolutional neural networks for satellite image classification. Through iterative development and testing, we achieved a 250% increase in accuracy from our initial Simple CNN to the final fine-tuned MobileNetV2 model. Prompt engineering played a critical role in guiding model selection, shaping labeling logic, and refining training strategies.
However, the process also revealed a key limitation: our relatively small dataset (452 images) restricted the model's ability to generalize, leading to misclassifications in visually ambiguous regions such as tree-lined parks or mixed-use land. To further improve the network, future work should focus on expanding the dataset, incorporating multispectral bands, and fine-tuning deeper layers of the model. These adjustments would increase both the precision and reliability of the classification system for real-world aviation and emergency response applications.

Related Literature

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