Computer Vision-Based Inspection for SDG&E Aviation Services

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Abstract

The reliable operation of electrical infrastructure is crucial for maintaining power distribution and preventing hazardous situations. This study presents an innovative approach to enhance the safety and efficiency of electrical asset management by leveraging computer vision techniques. We propose a model based on the pre-trained YOLOv11 (You Only Look Once version 11) architecture to identify obstructions in electrical assets automatically. Our method aims to detect various types of obstructions, such as vegetation encroachment, debris accumulation, and wildlife, which could potentially compromise the integrity of electrical equipment. By fine-tuning the YOLOv11 model on a custom dataset of electrical asset images, we develop a robust system capable of real-time obstruction detection. This approach offers significant advantages over traditional manual inspection methods, including increased accuracy, reduced inspection time, and improved safety for utility workers. The resulting model has the potential to revolutionize maintenance practices in the power industry by enabling proactive identification of potential hazards, thereby minimizing the risk of equipment failure and power outages. Our research contributes to the growing field of AI-assisted infrastructure management and paves the way for more resilient and efficient electrical grids.

Code: https://github.com/wkam3/Identifying-Obstruction-in-Power-Lines

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1 Introduction

In recent years, California has been faced with an intensifying amount of wildfires, largely influenced by urban development and fire-prone regions. A large contributor to these wildfire ignitions is electrical infrastructure when high winds, vegetation, and equipment failures can lead to devastating fires. To mitigate this risk, utility companies such as San Diego Gas & Electric (SDGE) have implemented Public Safety Power Shutoffs (PSPS), a strategy that involves de-energizing power lines during high-risk conditions. While PSPS has proven effective in reducing wildfire ignitions, it also poses far-reaching consequences, including economic losses and health risks for vulnerable populations. As wildfire threats continue to grow, there is a pressing need for proactive, data-driven approaches to assess and mitigate fire risks associated with electrical infrastructure.

A recent study, Utility Pole Fire Risk Inspection from 2D Street-Side Images, presents a computer vision-based framework for identifying wildfire risks associated with utility poles. In their paper, the authors utilize Google Street View imagery to detect poles, vegetation, and evaluate pole inclination, which can indicate structural vulnerability. By leveraging automated image analysis, the study provides a scalable method for prioritizing high-risk infrastructure and informing preventative measures, such as vegetation management and targeted undergrounding of power lines. This approach demonstrates how computer vision techniques can enhance wildfire mitigation efforts by identifying hazards before they lead to catastrophic events.

This study builds on that approach by integrating computer vision techniques to assess fire risks, focusing on detecting obstructions and identifying vulnerable electrical assets in real-time. The datasets that we are using contain infraction frequencies, outage frequencies, images of electrical assets, and obstructions on those assets. The dataset on infraction frequencies contains a count on all the different types of infractions that SDGE received for each of their electrical assets. With this, we intend to perform exploratory data analysis (EDA) to give us insight into the commonality of infractions. The outage frequencies dataset contains a count on all the different causes of outages with the electrical asset listed at fault. Like the infractions dataset, we will also use this dataset to help give us insight into the commonality of the different types of assets that cause outages. For the images, the electrical assets shown are objects, namely poles and wires, that are commonly dealt with daily. Obstructions on these assets include objects such as balloons and twigs that get commonly caught in the infrastructure. We then use these images to train, test, and validate a model capable of detecting obstructions in electrical assets.

2 Methodology

Our methodology for developing an obstruction detection system for electrical assets using YOLOv11 followed a structured pipeline combining computer vision best practices with modern deep learning techniques. YOLOv11, released in late 2024 by Ultralytics, represents the latest advancement in the YOLO (You Only Look Once) family of object detection models. As a Convolutional Neural Network (CNN), it builds upon its predecessors with significant improvements in architecture, efficiency, and accuracy. YOLOv11 introduces innovative features such as the C3k2 (Cross Stage Partial with kernel size 2) block, SPPF (Spatial Pyramid Pooling - Fast), and C2PSA (Convolutional block with Parallel Spatial Attention) components, which enhance feature extraction and improve model accuracy. We chose YOLOv11 for our project due to its superior performance in real-time object detection scenarios, which is crucial for identifying obstructions in poles and wires. YOLOv11 achieves higher mean Average Precision (mAP) on the COCO dataset while using 22% fewer parameters than YOLOv8m, making it computationally efficient without compromising accuracy. This efficiency is particularly beneficial for our application, as it allows for faster processing speeds—approximately 2% quicker than YOLOv10—enabling real-time detection of potential hazards. At its core, YOLOv11 employs a single-stage, anchor-free detection approach within its CNN architecture. It directly predicts bounding boxes and class probabilities for objects in a single forward pass through the neural network. This method eliminates the need for region proposal networks or anchor boxes, resulting in faster inference times and improved handling of objects at various scales. The model's architecture includes an improved backbone and neck design, which enhances its ability to extract relevant features from images, crucial for detecting diverse obstructions in power infrastructure.

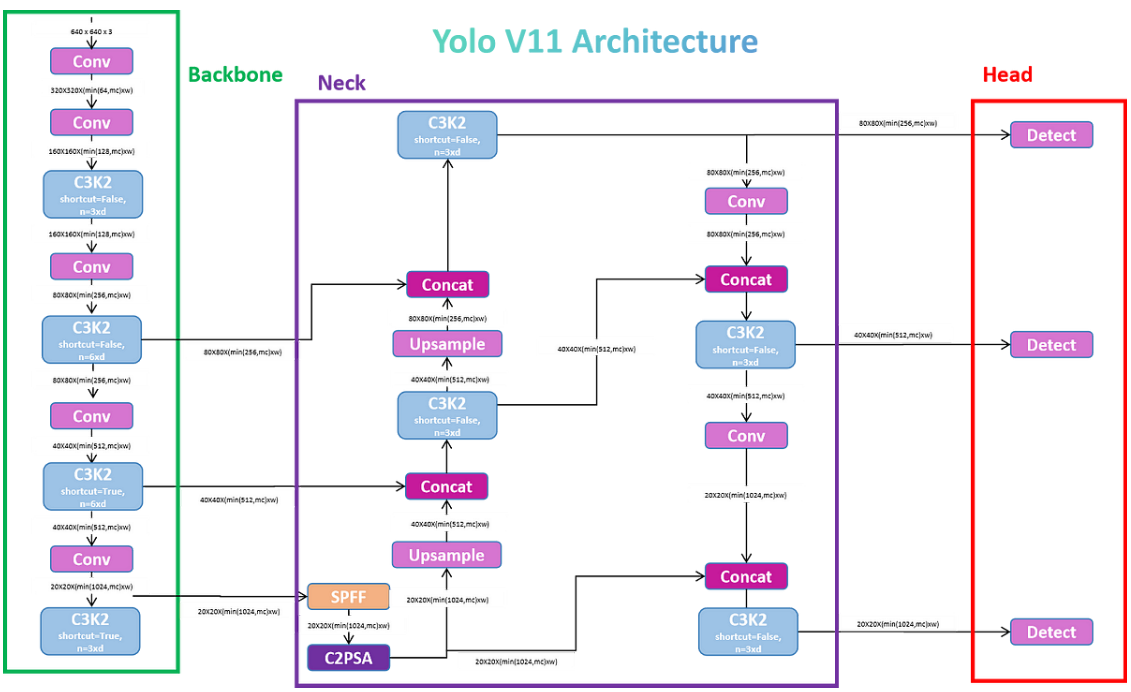

Figure 1: Yolov11 Architecture

The implementation of our models' consisted of five primary phases: EDA(exploratory data analysis), dataset curation, model configuration, training optimization, and performance evaluation. We first began by conducting EDA on outage data and infraction data per equipment type and we able to see that poles,conductors, and crossarms were the electrical assets that had the highest number of outages and infractions. We then began curating data for our model by gathering relevant videos and images then pipelining our images into a tool called Roboflow where we conducted image annotation. Yolo datasets comprise of both images and annotations as an additional json file. To create these annotations we drew bounding polygons for each of our images for each class we were labeling (poles, wires, obstructions). Roboflow provided user interface to perform these annotations as well as transforming our annotations into an accompanying json label dataset. We ended up compiling a dataset of 383 annotated images with an almost equal split between obstruction and non obstruction images. After creating our dataset we also included preprocessing steps as well as augmentations to generate more images. In our preprocessing we included auto-orient, resize, and contrast adjustment. Moreover, in our augmentation steps we performed both horizontal and vertical flips, rotations, shears, changes in hue, brightness, and exposure, blur, and noise. This resulted in an increase from 383 images to 1023 images. We then split our data into 94% training, 3% validation, and 3% test data. To train our model we took three different approaches. Our first approach was training directly on all of our labeled classes: poles, wires, and obstructions. Our second approach sought to use three different models for each respective class. These three models were independently trained on our full dataset to ensure optimal performance in each category. Following the training phase we applied each models' predictions to our test set and then implemented a NMS (Non-maximum suppression) strategy to refine our results and isolate our most confident predictions. This technique allowed us to retain only the most robust detections. Our final approach was training only on obstructions. We utilized a new dataset of only 81 images The parameters we used to train were 50 epochs, input image size of 416x416 pixels, batch sizes of 4, Automatic Mixed Precision enabled, and classes set to obstruction only. Following training we developed code to annotate our test images with our models' predictions and display metrics.

Notes: Train model with augmentation

3 Results

Our investigation into obstruction detection for electrical assets using YOLOv11 yielded insightful results across three distinct modeling approaches. Each approach offered unique perspectives on the challenge of identifying obstructions in complex electrical infrastructure environments.

3.1 Model Performance Comparison

Table 1: Validation Metrics Comparison Across Models

Metric	**Obstruction-Only**	**Multi-Class**	**Independent Models**
Precision	0.795	0.767	0.8956
Recall	0.571	0.692	0.5103
mAP50	0.629	0.721	0.5624

3.2 Obstruction-Only Model

The obstruction-only model emerged as our best-performing approach. By focusing exclusively on detecting obstructions, this model demonstrated superior performance in identifying potential hazards.

The high precision (0.9762) indicates that when the model identified an obstruction, it was correct 97.62% of the time. While the recall (0.5714) suggests room for improvement in detecting all obstructions, the model's ability to accurately identify obstructions when it did detect them was noteworthy.

3.3 Multi-Class Model (Poles, Wires, Obstructions)

Our multi-class model, trained to simultaneously detect poles, wires, and obstructions, showed lower performance compared to the obstruction-only model. While this approach provided a comprehensive view of the electrical infrastructure, it struggled with the complexity of distinguishing between multiple classes in often cluttered environments.

3.4 Independent Models for Each Class

Our approach using separate models for poles, wires, and obstructions, followed by NMS, yielded results that fell between the other two approaches. This method showed improvements over the multi-class model but still fell short of the obstruction-only model's performance.

4 Discussion

Our investigation into obstruction detection for electrical assets using YOLOv11 yielded several important insights:

4.1 Focus on Visual Results

While quantitative metrics provide valuable insights, we found that visual results were particularly crucial in assessing model performance. The obstruction-only model's ability to accurately highlight potential hazards in images proved more valuable than marginal improvements in numerical metrics.

4.2 Challenges with Context

Our experiments revealed that incorporating contextual elements like wires and poles into the detection task introduced additional complexity. The multi-class and independent models, while theoretically more comprehensive, struggled with the noise and variability inherent in electrical infrastructure imagery.

4.3 Simplicity in Approach

The superior performance of the obstruction-only model suggests that for tasks with significant visual noise and complexity, focusing on a single, critical class may yield better results. This finding is particularly relevant for real-world applications where clear, actionable detections are more valuable than comprehensive but potentially confusing multi-class predictions.

4.4 Practical Implications

These results are highly relevant for the practical implementation of AI in electrical infrastructure maintenance. The obstruction-only model's high precision suggests it could be effectively deployed to quickly identify potential hazards, allowing for more efficient allocation of maintenance resources and potentially reducing the risk of power outages or safety incidents.

4.5 Future Work

While the obstruction-only model performed best in our tests, there's significant potential for further improvement, particularly in light of critical business needs. The delicate balance between precision and recall is crucial in this context: false positives could lead to unnecessary resource allocation and increased operational costs, while missed obstructions could result in potential hazards remaining unaddressed.

Future work should focus on enhancing recall without sacrificing the high precision achieved, aiming for a model that minimizes both false positives and false negatives. This could be achieved through:

- Incorporation of more diverse training data, particularly images capturing a wide range of obstruction scenarios and environmental conditions.
- Implementation of advanced data augmentation techniques to improve the model's robustness to various real-world situations.
- Fine-tuning of the model's confidence thresholds to optimize the precision-recall trade-off for operational requirements.

Moreover, to transition from a proof-of-concept to a practical tool, future development should focus on integrating this model into a user-friendly interface or application. This application should be designed for deployment on drones, enabling real-time obstruction detection during aerial inspections of power lines. Such an integration would require optimizing the model for edge computing, ensuring it can operate efficiently with the computational constraints of drone hardware while maintaining real-time performance.

4.6 Conclusion

Our findings underscore the importance of tailoring the modeling approach to the specific needs of the task at hand. In the context of electrical asset management, the ability to reliably detect obstructions proved more valuable than a more comprehensive but potentially less accurate multi-class detection system.

5 Appendix

Computer Vision-Based Inspection for SDG&E Aviation Services (Proposal)

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1 Broad Problem Statement

One of the many responsibilities of San Diego Gas & Electric's Aviation Services department are manual helicopter inspections which are a critical, yet inefficient and hazardous part of SDG&E's infrastructure maintenance. Inspectors visually examine power lines and conductor spans by flying low to the ground to identify damage or obstructions such as fallen branches or deteriorating wires. This process is slow, costly, and heavily reliant on human judgment, which can lead to missed defects or errors, especially in urgent situations such as wildfire seasons. Timely identification of impacted assets can reduce wildfire risks, improve system reliability, and enhance the safety of inspection teams. Computer vision provides an opportunity to automate this process, significantly reducing reliance on human labor. By leveraging aerial drone footage and advanced object detection algorithms, we can create a tool that pinpoints impacted assets in real time, providing accurate maintenance data and revolutionizing inspection methods.

2 Narrow/Technical Problem Statement

This project proposes to fine-tune and train a YOLOv8 object detection model to distinguish between impacted and non-impacted assets from aerial footage. For this purpose, impacted assets include utility infrastructure with visible damage or obstructions, such as fallen trees on power lines, snapped wires, or corrosion on conductor spans. The goal is to create a system that can process video footage frame by frame and detect and label these anomalies. The project will involve high-quality data for training and improving a baseline model, including publicly available images sourced from Google Images. These will include images of impacted power lines, conductor spans, and common obstructions (e.g., fallen branches) as well as non-impacted assets. The team will validate this dataset with SDG&E mentors to ensure it includes sufficient variation in environmental conditions, asset types, and damage categories. Additionally, we plan to reach out to SDG&E for access to real-world aerial footage, ensuring that the model generalizes well to domain-specific use cases.

The technical challenges of this project include:

1. Data Collection and Annotation:
   - Google Images will serve as an initial source of training data
   - Domain-specific aerial footage is critical for accuracy
   - Dataset will include high-resolution images of impacted and non-impacted assets
   - Images will be annotated with bounding boxes to train the YOLOv8 model
2. Model Training:
   - YOLOv8 will be fine-tuned using transfer learning
   - This allows adaptation from general-purpose knowledge to utility asset inspection
   - Model performance will be evaluated using metrics such as mean Average Precision (mAP) and confusion matrices

- UCSD's rented cloud servers (AWS) will be used to execute the code

3. Integration with Aerial Footage:
    - Trained model will be tested on video sequences
    - Process involves extracting frames, detecting impacted assets, and visualizing results

Our Q1 project analyzed geographic data to predict the probability of Public Safety Power Shutoffs (PSPS) due to varying environmental conditions, but failed to address other ways to mitigate wildfire risk and measures we can take to reduce the number of shutoffs. Our approach in this project builds upon existing advancements in computer vision and object detection but uniquely focuses on fine-tuning these methods for utility infrastructure, a domain where data scarcity and variability pose significant challenges. Unlike current solutions that rely on human review of aerial footage, this project aims to automate the process entirely, enhancing efficiency and scalability.

3 Primary Output Statement

The primary output of this project will be an interactive interface that processes video footage to identify impacted and non-impacted assets. The interface will allow users to upload aerial videos (e.g., helicopter or drone footage) and replay them with bounding boxes overlaid on identified impacted assets. For example, in a video showing a power line with a fallen branch, the system will automatically label the obstruction, highlighting it in the replay. While the initial focus will be on helicopter footage, the interface could later be extended to integrate drone footage for fully autonomous inspection along utility lines. Future iterations may also explore real-time video analysis for immediate detection during flight.

6 Contributions

Will: Found and Annotated 300 images. Wrote abstract, methodology, results, and discussion section. Decided on preprocessing and augmentation strategies as well as trained 5 preliminary models. Integrated and annotated video data into models. Developed an additional instance segmentation model focusing on identifying poles and wires. Took code from notebook and refactored into expected code structure (script.py, functions.py, config.json). Tested and wrote edited instructions to run our script. Developed three model approach. Wrote text for poseter and created some visualizations.

Gregory Quach: Uploaded and Annotated data from videos, and images. Wrote Introduction in the report. Completed the EDA on new data. Figured out a way to get predictions on videos. Created model based on videos. Worked on code for the computer vision model to run locally.

Bharath Sathappan: Uploaded and Annotated 100 images. Researched different computer vision models and decided on YOLOv8. Trained and tested different augmentation and preprocessing strategies in jupyter notebook for 3 different strategies across 3 different models. Developed front-end visualizations and bounding box drawings of model predictions.