CERA: A Community-Driven Platform for Enhancing Utility Safety

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Abstract

As readily available electricity grows in the essential role it plays in functioning society, mitigating potential power outages by way of faulty electric poles is a top priority for utility companies. Raising alerts on deficient electric structures not only ensures the continued distribution of electricity but also prevents safety hazards, such as wildfires and road blockages. Current utility management relies largely on the general public to report potentially dangerous equipment through phone calls, which are beneficial as a baseline alert and evaluation. However, response teams at companies like SDG&E are not able to fully assess the problem without first sending out teams to inspect the damage, which is resource-intensive and time-consuming. Our project attempts to optimize this system by envisioning a platform where members of the public can submit images and a description of problems they see with poles, with machine learning models that will evaluate this information to determine the degree of urgency of the equipment's condition. Rather than create the platform itself, this paper represents a proof of concept, with the application of three models on sample and manually derived data. To account for the diversity of images that may come from a public platform or app, we optimized a pre-trained object detection model to identify poles from images with a variety of qualities. To then gain insights from given text descriptions of the problem, we applied two natural language processing (NLP) models on sample disaster tweet data to gauge the topic and sentiment from reports. Applying these models serves as evidence of the potential that manual platforms for reporting electrical structures promise for utility companies in the future.

Code: https://github.com/kellyhpark/Pole-Validation

1 Introduction

Loss of electricity proves to be a hazard to both the safety and function of the communities that it supports. Oftentimes, power outages and rare, yet deadly wildfires begin with malfunctioning electrical structures. With the sheer abundance of electric poles and underground structures, the general public thus plays an essential role in reporting faulty equipment to utility companies and keeping their communities safe (SDGE 2024). For many service providers, existing real-time customer communication involving potentially harmful equipment malfunctions is accomplished by providing a phone number to call in to report visible or audible problems. While reporting by call is adequate in the insight that can be gained about the issue by directly speaking to customers, discrepancies exist with the lack of visual data on the faulty equipment. Calls with responders to utility damage reports may be susceptible to confusion and miscommunication due to the lack of domain knowledge that members of the general public would have in describing the situation before them, and to then accurately assess the issue, utility experts would need to physically inspect the structure. As a result, customer assistance is resource intensive as a crew must drive out for customer reports that may not have needed immediate attention, costing time and money.

In this area, we aim to assist the cross-section of customer service and computer vision, as well as natural language processing (NLP). Our response was a platform, CERA, that would allow the customer to have a greater voice in aiding their community, and provide them an outlet to send information straight to utility professionals without the need for companies like SDG&E to send out a field agent for every call. In this paper, we train three machine learning models to replicate the validation functionalities that a potential reporting app might utilize to gauge the urgency of a recent report. To do so, we first optimized an existing object detection model by training it further with more than 500 manually collected images of poles from different angles, lighting, and closeups. We then trained two NLP models on tweet data sourced from the time of various natural disasters to observe the capabilities of such models to then identify the topic and urgency of potential pole issue descriptions that the reporting app or platform would accept. To the extent of our knowledge, no similar functional technology is in use at SDG&E, and through this proof of concept, we aim to display the potential of utilizing machine learning to optimize utility reporting.

2 Methods

In order to replicate the expected usage of a potential app that is fully developed and used in the real world, we considered many factors from both the user's and utility expert's perspectives. We considered various machine learning models for object detection, including DETR, a model developed by Facebook, known for its accuracy and robustness, which we ultimately selected (Rustamy 2023). In implementing NLP models, we researched Word2Vec, sentence transformers, and considered utilizing the GPT API to identify which would best suit our needs. Eventually, the VADER sentiment analysis model, along with the Support Vector Machine (SVM) model for topic classification were selected for the text analysis step, as they were best suited to return the desired results we were looking to obtain from inputting pole issue descriptions.

2.1 Data Collection

To optimize the DETR model and train both NLP models, data collection was a significant concern for proving the potential of the theoretical platform which our paper is based upon. Although DETR is a pre-trained model, we required images of poles that emulated those that might be taken by users who lack domain knowledge of object detection. Thus, data collection for the pole validation model involved manually collecting images of poles found throughout La Jolla. By taking photos from different angles, times of day, and exposures, we compiled 515 photos that were subsequently labeled using CVAT, an image labeling tool. By taking different styles of images, we attempted to train DETR to recognize poles despite unsatisfactory image quality. While we recognize that our manually collected training set does not account for all environments in which poles may exist, or comprehensively reflect those in the SDG&E service area, for this paper we aim to present its base capabilities simply. In further researching data that could be used to train NLP models, we located a HumAID disaster dataset, composed of tweets made during natural disasters, categorized across 11 humanitarian classifications (Firoj Alam and Ofli 2021). Because we required labeled data that would be similar to written pole reports from users in their brevity and urgency concerning electricity and broken infrastructure, this dataset serves our purposes well.

2.2 Model Development

The first layer of the product validates whether or not the image contains a pole, and the DETR model was thus optimized to be able to do so. In intentionally collecting images that varied in quality, we attempted to accommodate many different users of the platform, including those who cannot take perfect photos, such as older customers, as well as those who locate faulty poles at unfavorable times of day. In addition, there may be users who submit images that do not contain any poles, taking pictures for the sake of inputting random images. By training the model to recognize those photos that are not best suited for object detection and filter out images that have no actual value to SDG&E, we aimed to prove that this potential pitfall of the app is accounted for. In doing so, the DETR model was further trained on our custom dataset and identified poles if the confidence surpassed 0.7 (Woctezuma 2023).

In addition to images, we recognize that text is an additional resource that can be used to capture the elements that are not detectable in an image. For example, users could include information such as “it makes a buzzing noise” or “there are sparks coming out the top”. With this there were two applications we chose to pursue, topic classification with a Support Vector Machine (SVM) and sentiment analysis with a VADER model. They will both contribute to the decision-making on how urgent the condition of the pole is and how the information will be presented to the industry expert for human review in a potential app.

For sentiment analysis using VADER, we first applied the model to a subsection of HumAID tweet texts to simply observe the model's capabilities. Because the VADER model is pre-trained, and thus does not need to be fit on a training dataset unlike many other machine learning models, the HumAID dataset did not serve any other purpose other than to observe VADER performance. However, while disaster tweets helped gauge the capability of sentiment analysis methods, future use of this form of analysis in CERA would require greater sensitivity to pole or electric structure-related words. To do so, we customized the VADER model to associate specific pole-related words with varying negativity or positivity scores on a range from -4 to 4. Among these words included "collision", "lean", "outage", and "wire". By optimizing the model to take certain words with greater, or lesser weight in calculating a sentiment score, we desired to prove one additional way NLP can aid in gauging the urgency of a report. After doing so, we then created a small dataset of artificial pole reports, emulating ones CERA may receive from a real user. After cleaning the text data by lemmatizing, a form of stripping words in the text to their simpler form, and by then applying VADER to each mock issue description, we examined the model's evaluation of the sentiment.

Lastly, in the topic classification stage of the paper, the SVM model was trained on HumAID data to distinguish between the following two topics from a given report text: "requests or urgent needs" and "infrastructure and utility damage". Because not all of the humanitarian categories that the dataset offers tweets of are relevant to topics that may be seen in pole-related issue descriptions, we filtered for only those records that more closely align with our vision for CERA's capabilities. In utilizing SVM, we split the data into train and test sets and cleaned the text by removing capitalization, punctuation and rogue characters, and stopwords. We then deployed the training set through a pipeline of CountVectorizer to turn each tweet text into a matrix for unique word counts, a TFIDFTransformer to transfer the count matrices into a TF-IDF format, and finally a linear SVM classifier. After training, the model's performance on the test set was observed. As a final measure of evaluation, SVM was trialed on a minimal dataset of artificial pole reports, much like the one used in the VADER sentiment analysis portion (Li 2018).

2.3 Platform Design

The platform, CERA, was conceptualized as a solution to bridge community insights, technological innovation, and expert analysis in addressing utility infrastructure risks. While the platform itself was not fully developed, we conducted extensive research and design work to outline its structure and functionality. Our key design principles are aimed at ensuring user safety, empowerment, efficiency, transparency, and continuous improvement (ProductPlan 2024).

CERA's user experience (Figure 1) is designed to be simple and user-friendly, empowering users to contribute to their communities' safety and functionality. Efficiency and transparency are also central to CERA's design, with the platform leveraging machine learning models to prioritize urgent cases and provide clear communication to utility teams. Moreover, CERA is committed to continuous improvement, with plans for ongoing iteration and refinement based on feedback from users.

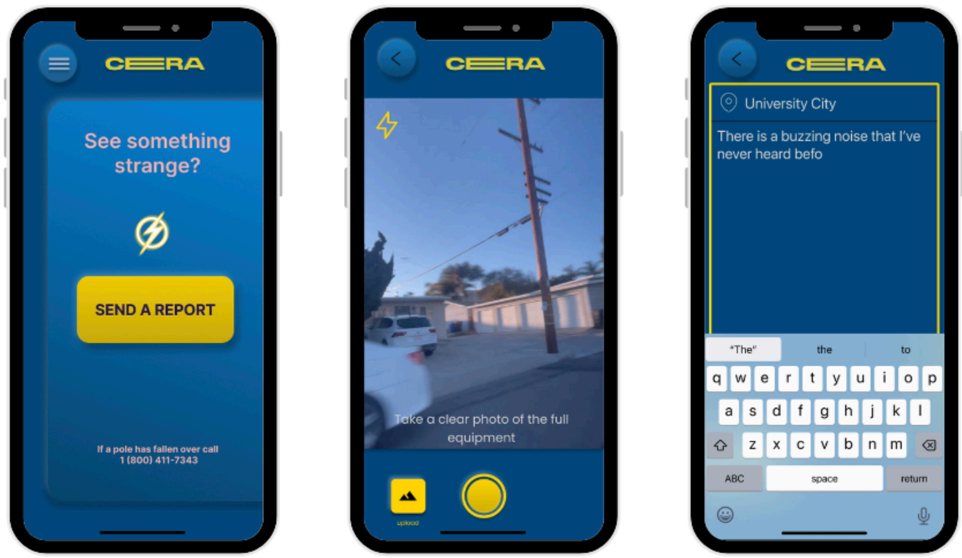

Figure 1: Sample pages from CERA user interface design

CERA seamlessly integrates the machine learning models within its user interface, facilitating efficient reporting of utility pole issues. The user flow chart (Figure 2) illustrates the streamlined interaction between users and the three integrated machine learning models, ensuring a straightforward reporting process.

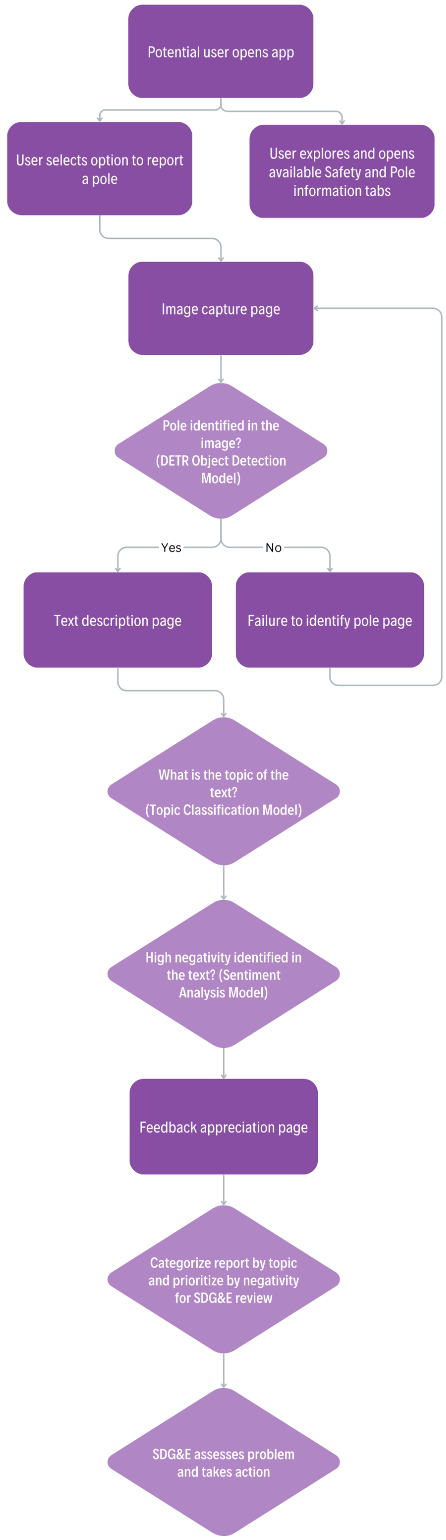

Figure 2: CERA platform pipeline

3 Results

3.1 DETR Object Detection Results

DETR object detection upon training on 515 images of labeled overhead structures displayed a consistent decrease in loss over the 10 epochs, while performance on the validation set produced a more erratic trend. In Figure 3, results from the fourth and ninth epochs appear to have the least loss. On the other hand, the mean average precision (mAP) performance displayed an overall upward trend with a significant drop in precision at the fifth epoch (Figure 3). After 10 epochs, select labeled results of the DETR model on unseen images are seen in Figure 4. While the model incorrectly mistook a tree in the background with a considerably high confidence of 0.91 in the left photo, the model identifies the pole correctly in the second image despite the unfavorable lighting. In other images in the validation set, the model appears to have no trouble identifying poles in the photo particularly when they have identifiable markers such as yellow bands or ID numbers across their base. While confusion between trees and wooden poles is a misstep for the DETR model, the mistake is infrequent, and the model often was shown to display a commendable capability to distinguish between the two.

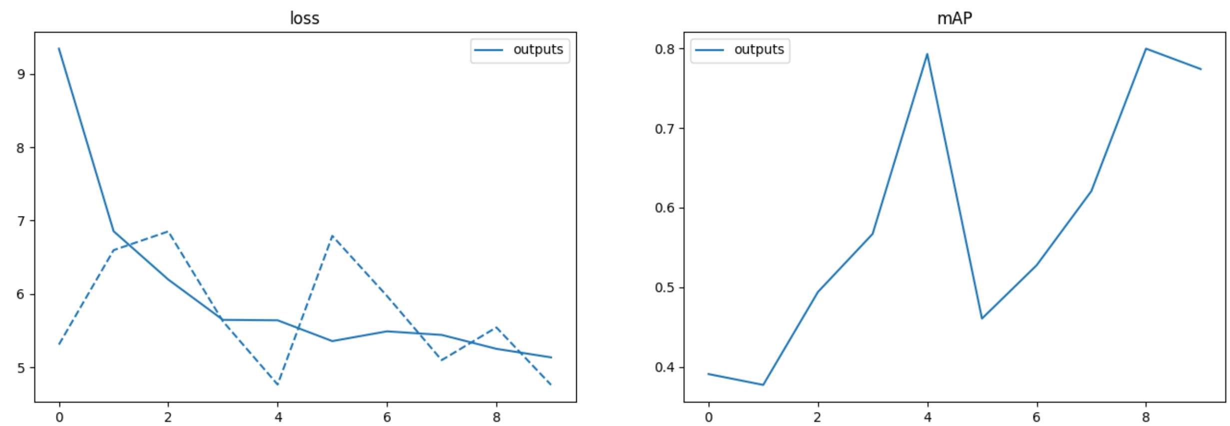

Figure 3: Graphs for DETR object detection loss and mAP

Figure 4: Label prediction on validation set

3.2 NLP Model Results

The SVM topic classification model resulted in an accuracy of 98% on the HumAID test data after being trained to differentiate between ”request or urgent needs” and ”infrastructure and utility damage” (Figure 5). In further validating the model on the minimal dataset of artificial pole reviews mentioned in Section 2, the model returns an incorrect classification of four out of thirteen pole reports, all of which fell under the ”requests or urgent needs”. This seems to reflect the model’s slight deficiency in identifying the more urgent, humanitarian reports in contrast to the infrastructure-related ones.

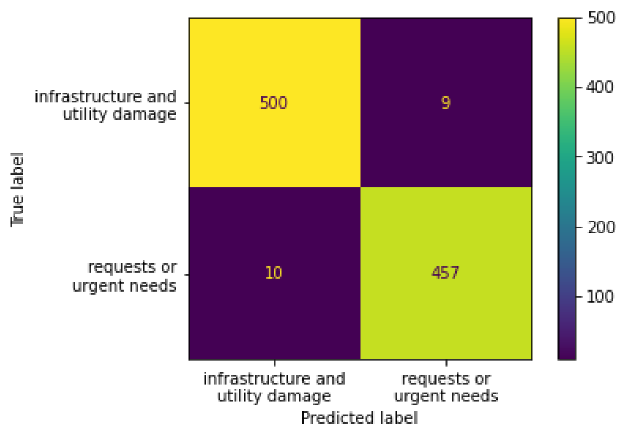

Figure 5: SVM topic classification confusion matrix

Lastly, because the VADER sentiment analysis model is a pre-trained model, we need only to observe the results on the text it is given (Beri 2020). On a section of the HumAID data, the model appeared to understand the nuances and exaggerations of the tweets to a considerable level of accuracy. This level of perception, when the VADER model was customized with pole issue-related words, seems to have carried over. For example, upon giving it the sample report of ”I saw this pole next to a tree, and it seemed too exposed to the weather”, the model evaluated it with a compound score of -0.3182, giving it an overall negative sentiment. While an uncustomized VADER would have evaluated the text as neutral, we observed that the model is conscious of the desired nuances. However, despite its successes, the model, when given combined levels of positive and negative sentiments, still displays a vulnerability to mistaken evaluations of the overall sentiment.

4 Discussion

The optimization of the DETR model to validate the presence of a utility pole in submitted images reflects a crucial first step in ensuring the platform’s effectiveness. Through this step, we managed to filter through irrelevant submissions, ensuring that only appropriate reports reach utility providers like SDG&E. The DETR object detection model, despite its high potential, exhibits limitations in differentiating between trees and wooden utility poles. While the model's performance is commendable, it signifies the need for ongoing model refinement and an expanded dataset that encompasses a broader spectrum of scenarios. Enhancing the model's accuracy could involve creating a more specific training set that better distinguishes between trees and wooden utility poles.

The SVM topic classification model, with its impressive accuracy, showcases the power of machine learning in categorizing text data efficiently. However, its current binary labeling system limits its comprehensive applicability in real-world scenarios. To enhance the model's utility, our future focus will involve gathering user data to develop a robust training set. This set will encompass a wider array of labels, reflecting the diverse range of issues users might report. This evolution will not only refine the model's accuracy but also extend its practicality, making the platform significantly more beneficial for users and utility providers alike.

The VADER sentiment analysis, tailored to prioritize pole-related issues, highlights the adaptability of sentiment analysis tools in focusing on domain-specific challenges. This customization aligns with contemporary sentiment analysis applications, showcasing the model's flexibility and potential impact in prioritizing reports based on sentiment scores. We assigned scores based on our best judgment of how significant these words are when talking about pole issues. However, this method is quite subjective and introduces some uncertainty, because we haven't tested whether our assigned scores truly reflect how these words are used in the context of reporting utility pole problems. This means there's a bit of guesswork involved in how accurately these scores represent the actual sentiments conveyed in the reports.

Comparing our results with existing utility management practices, CERA introduces a novel approach by integrating community engagement with machine learning. This contrasts with traditional methods that heavily rely on scheduled inspections or customer reports via phone calls.

Looking ahead, future research should explore expanding CERA's capabilities to include a broader spectrum of utility infrastructure, beyond poles, to include pipelines, electrical substations, and other critical components. Advanced machine learning techniques, such as deep learning and generative AI, could be employed to improve the platform's analytical depth and predictive accuracy. Furthermore, the integration of real-time data feeds, such as weather conditions or historical maintenance records, could enhance the platform's contextual awareness and decision-making processes.

5 Conclusion

In this paper, we have shown that the utilized combination of machine learning models including DETR, SVM, and VADER serve as an effective proof of concept for the future of utility reporting. In the conception of CERA, the initial groundwork of validation for the image and text portions of the report process has been set, in the accuracy and base functionality of the models selected. This sets the foundation for further expansion of the platform in future development as more crowdsourced data becomes available with the platform's deployment. As discussed in Section 4, CERA contains the potential for more specific, more accurate models, that would set utility companies like SDG&E to better protect the communities within their service areas while allowing the customer to play a greater role in keeping their neighborhoods supplied with the electrical resources needed to function, and the safety necessary to thrive.

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