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Project Title

Intelligent Safety Assessment of Rural Roadways Using Automated Image and Video Analysis

University

University of Utah

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Research Needs

According to statistics reported by the department of public safety of Utah for 2018, 62,074 motor vehicle crashes occurred statewide, resulting in 237 fatalities and 25,645 injuries [1]. Road conditions and driver behaviors are two major causes of crashes. In this regard, roadside features play a vital role in road safety. Specifically, severe sideslopes (greater than 4:1), presence of obstacles (trees, poles, houses, etc.), and lack of safety barriers or guard rails are among the attributes that may affect road safety. As an illustrative example, Figure 1 shows a road segment with a dangerous side slope.

Due to the significant effect of roadside safety on the number and severity of road accidents, many state DOTs are trying to detect road segments with potentially unsafe roadside attributes. This can be achieved by manually inspecting videos and images collected by third-party data providers, such as Mandli. However, this process is both time-consuming and susceptible to human error. Therefore, an automated approach that leverages computer vision and machine learning would be an efficient and more accurate alternative.

In recent years, many transportation-related problems were tackled using computer vision. Pavement monitoring, vehicle detection, road safety, and asset management are some of the topics that researchers have tackled using various algorithms, including Convolutional Neural Network

(CNN) and Deep Neural Network (DNN). Thanks to vast imagery and video data collected on our roads, these algorithms can also be used to facilitate the process of evaluating roadside features. To this end, we propose development of an automated approach that leverages computer vision and machine learning to rate rural roadways based on different roadside safety criteria (e.g., side slope, guardrails, road lines, obstacles, signs).

Figure 1. A Rural Roadway with Severe Side Slope

Based on the images and videos collected by Mandli, a deep learning model can be developed to detect and evaluate parameters affecting roadside safety. Some of the considered parameters are: Sideslopes (acceptable, unacceptable, no slopes), Shoulder width (acceptable, unacceptable, no zone), Shoulder condition (acceptable, unacceptable), Clear zones (acceptable, unacceptable, no zone), Guardrails (Yes, No). In addition, the automatically processed data can be used to rate each road segment using roadside safety systems of different organizations. For example, the Federal Highway Administration (FHWA) suggests a rating of 1 (best) to 7 (worst), while the U.S. road assessment program (USRAP) uses a 1-5 scale to rate the safety of each road segment.

The proposed method would enable UDOT engineers to quickly screen the local road network for "problematic locations" and prioritize projects aimed at improving safety levels (e.g., remove trees, add guardrails). Figures 2 and 3 provide example applications of the envisioned model, which would be used to completely automate roadside rating, thereby removing the need for human labor.

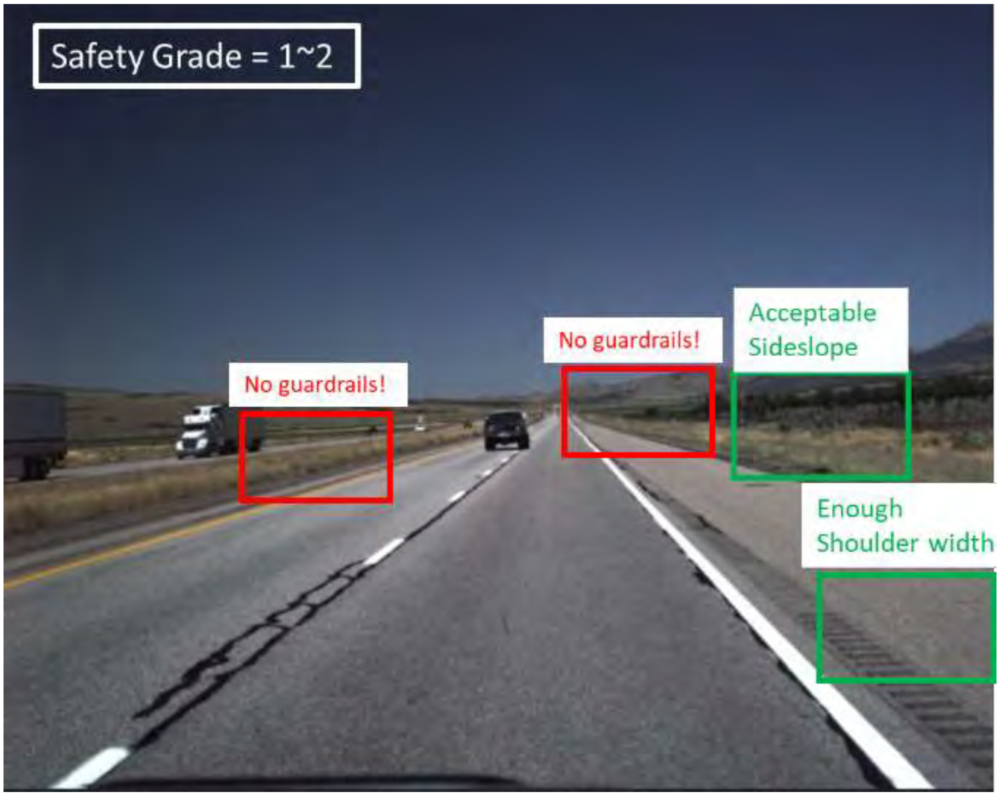

Figure 2. Year 2019 - Roadway 15- Mileage 127.84

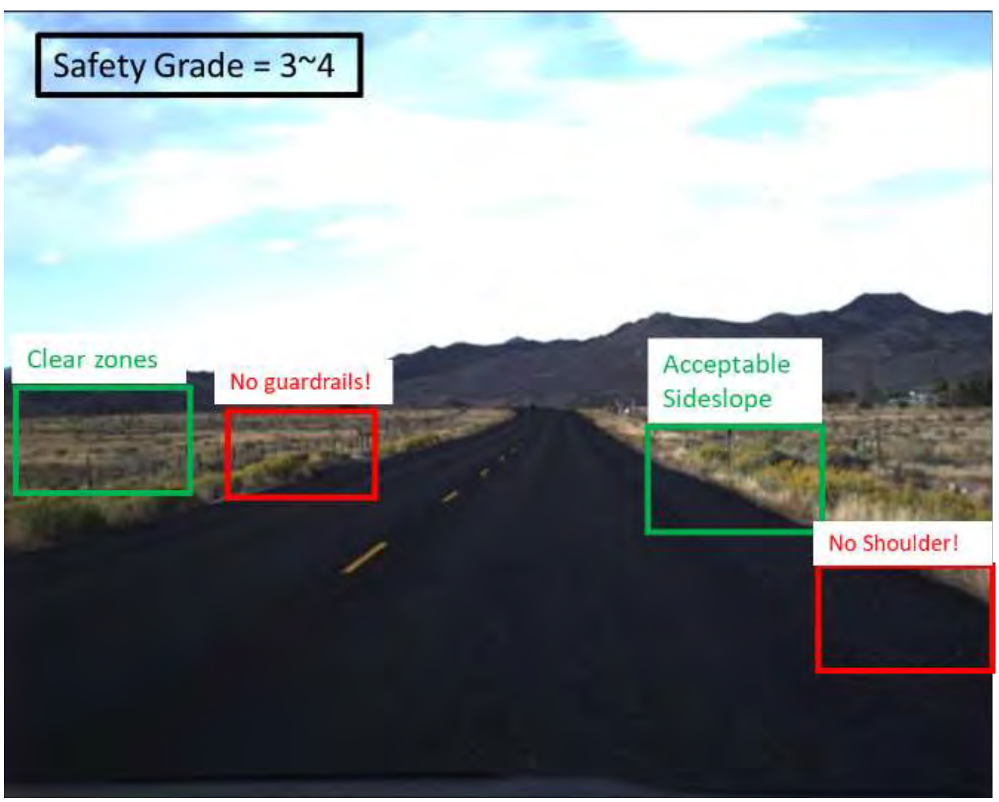

Figure 3. Year 2019- Roadway 89 - Mileage 178.74

Research Objectives

The objective of this research project is twofold:

1. Developing a computer vision-based model to detect roadside problems and automatically rank road segment safety based on different ranking systems;
2. Provide UDOT engineers with prototype software that UDOT engineers will be able to apply to new batches of Mandlii images.

Research Methods

The proposed model consists of the following steps:

1. **Collecting the required data**, including images and videos taken by Mandli;
2. **Data Labeling:** The safety parameters within a small group of images will be detected and labeled manually in order to develop the machine learning model;
3. **Preprocessing Data**;
4. **Training machine learning algorithms** using the labeled data;
5. **Evaluating** the performance of the model.

More details about each step are provided next.

i) Data Collection

A valuable resource for detecting unsafe road segments are the videos and images collected by Mandli. Mandli is a specialized highway data collection company that integrates 3D pavement technology, mobile LiDAR, and geospatial equipment for multiple departments of transportation throughout the U.S. This valuable source of data could be used to assess safety parameters along each road segment in the state of Utah. Figure 4 shows one of the vehicles that Mandli Company uses for taking images and videos of roadways.

Figure 4. Mandli X35 Collects Highly Detailed Data

As shown in Figure 4, there are six attachments to the vehicle. Figure 5 shows an image taken by Mandli. The following will explain their role.

1. Dual Velodyne HDL-32 LiDAR sensors
2. Nine 8.9 MP Cameras deliver nearly 80 megapixels of a 360° image
3. Dual LCMS Pavement Scanners
4. Position Orientation System
5. Advanced independent Power System
6. Processing/Post-Processing Software [2]

Figure 5. Highway I15, Mileage 100.0497

ii) Data Labeling

Data labeling consists of manually annotating content with tags and labels. This is usually done by humans and requires a lot of time and effort. In this step, the label will identify the fault and safety issues within the image. The labeled data could then be used to train a supervised learning model. Data labeling is critical for the success of machine and deep learning models. Erroneous labels introduce noise to the data and can cause a model to fail.

iii) Preprocessing

For certain features, such as shoulder width, some preprocessing may be required. An example processing aimed at filtering the input image to a specific output is described in Figure 6. Furthermore, an example of a raw and filtered image are shown in Figure 7.

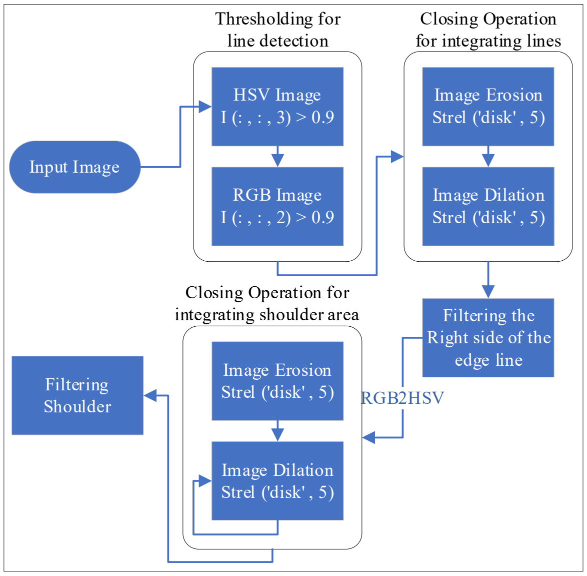

Figure 6. The Process of Filtering Images for Shoulder Width Detection

Figure 7. An Example of Image Filtering for Specific Safety Issues

iv) Model Training

Using the labeled images, we can develop a convolutional neural network (CNN) to classify and rank images. There are various types of models that are based on CNN. Figure 8 shows AlexNet as an example of CNN models.

- Region Proposals (R-CNN [3], Fast R-CNN [4], Faster R-CNN [5], cascade R-CNN [6])
- You Only Look Once (YOLO) [7]
- Retina-Net [8]

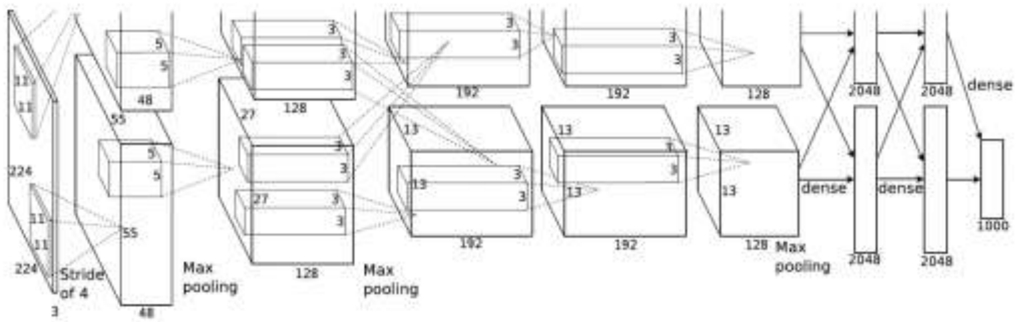

Figure 8. AlexNet Structure (2012 winner of ImageNet Competition) [9]

As shown in Figure 8, different layers have been used in CNN models to improve their performance. Next, we list the four common layers and their role in CNNs.

1. Convolution Layer: Convolve the input image with a specified kernel
2. Activation Layer: Activation functions are added into neural networks in order to add nonlinearity into the model
3. Max Pooling: Reducing the size of images in the deep layers to save us from unnecessary computational expenses
4. Flattening: Converting the 2D array into a 1D array

v) Model Evaluation

Finally, the model performance is evaluated using different metrics. The following are the most common evaluation metrics:

1. Accuracy, Precision, and Recall
2. F1 Score
3. Log Loss/Binary Crossentropy
4. Categorical Crossentropy
5. AUC

Expected Outcomes

The expected outcomes for this project will include the following items: A report consisting of the literature review, methodology, results, and performance evaluation; a GIS shapefile indicating roadside safety ratings for all state roads in rural areas; a prototype for outsourcing safety management functions. Moreover, the outcomes of this project will be discussed and evaluated by UDOT practitioners who will directly benefit from this project.

Relevance to Strategic Goals

Automatic detection and ranking of roadside safety will help UDOT engineers develop a comprehensive list of roadways with poor safety conditions. Moreover, the suggested method will be capable of ranking roadsides based on different safety ranking systems, such as FHWA and USRAP, which would be complicated and time-consuming for a human to do. Furthermore, applying the proposed method will enable UDOT to quickly screen road networks for safety issues and make more informed decisions when prioritizing different safety-improvement projects.

Educational Benefits

Dr. Nikola Markovic and Dr. Abbas Rashidi are assistant professors at the University of Utah, working on applying computer science techniques to different civil engineering tasks. The research team has been involved in several projects to analyze images and video data using computer vision algorithms. The PIs of this project are currently teaching two graduate-level classes called "CVEEN 6530: Quantitative Methods for Transportation Operations" and "CVEEN 6790: Advanced Computer-Aided Construction". It is expected that the developed algorithms, methods, and case studies will be directly converted into new course materials for these courses. In addition, several undergraduate and graduate students will be participating in different steps of this project, including data collection, processing, and validating the obtained results.

Technology Transfer

The technology transfer process for this project will take place through two major channels: 1) publishing scholarly journal papers (conference proceedings); 2) direct interactions with UDOT staff as the potential end-users for the results of this study; 3) providing UDOT engineers with a prototype software to facilitate future applications of the model.

Work Plan

The project will include the following major tasks:

1) Literature review and evaluation of the existing approaches; August and September 2021
2) Extracting a list of road safety problems listed in the literature; August - October 2021
3) Data collection and labeling; September 2021 – March 2022
4) Providing the necessary hardware settings; September 2021
5) Developing machine and deep learning models; February - July 2022
6) Model evaluation and discussion; March - August 2022
7) Writing report; September 2022
8) Report revision; October 2022

Project Cost

Total Project Costs:	$81,000
MPC Funds Requested:	$36,000
Matching Funds:	$45,000
Source of Matching Funds:	Utah Department of Transportation, financial support

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