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INTELLIGENT SAFETY ASSESSMENT OF RURAL ROADWAYS USING AUTOMATED IMAGE AND VIDEO ANALYSIS

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16. Abstract

Roadside safety is a critical aspect of transportation management, with elements like rigid obstacles, guardrails, clear zones, and side slopes significantly impacting accident outcomes. The Federal Highway Administration (FHWA) provides a valuable rating system for Department of Transportation (DOTs), but the manual rating process is time-consuming and prone to inconsistencies. This project introduces an innovative solution employing computer vision and machine learning algorithms to automate the roadside safety evaluation process. Utilizing pre-trained models such as VGG16 and images captured from Utah roadways, the research team develops a robust algorithm for automated safety evaluation that aligns with the FHWA rating system, providing a comprehensive and efficient method for assessing roadside conditions. Tailored computer vision algorithms detect specific features, enhancing the accuracy of safety evaluations. Pre-trained models for clear zone detection and roadside slope classification further contribute to a nuanced understanding of roadside elements. The project's outcome is a shapefile containing safety rankings for road segments on five state roads. This tool empowers traffic engineers with data-driven insights, enabling informed decision-making for prioritizing improvement projects and enhancing road safety. The automated approach showcased in this research offers a promising avenue for strengthening roadside safety measures and preventing potential accidents. While acknowledging challenges such as periodic retraining and potential false positives, this approach stands as a promising addition to existing methods. The study culminates in a shapefile encompassing safety rankings, roadside features, and illustrative sample images, providing a tangible tool for UDOT in optimizing road safety strategies.

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

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ABSTRACT

Roadside safety is a critical aspect of transportation management, with elements like rigid obstacles, guardrails, clear zones, and side slopes significantly impacting accident outcomes. The Federal Highway Administration (FHWA) provides a valuable rating system for departments of transportation (DOTs), but the manual rating process is time-consuming and prone to inconsistencies. This project introduces an innovative solution employing computer vision and machine learning algorithms to automate the roadside safety evaluation process. Utilizing pretrained models such as VGG16 and images captured from Utah roadways, the research team develops a robust algorithm for automated safety evaluation that aligns with the FHWA rating system, providing a comprehensive and efficient method for assessing roadside conditions. Tailored computer vision algorithms detect specific features, enhancing the accuracy of safety evaluations. Pretrained models for clear zone detection and roadside slope classification further contribute to a nuanced understanding of roadside elements. The project's outcome is a shapefile containing safety rankings for road segments on five state roads. This tool empowers traffic engineers with data-driven insights, enabling informed decision-making for prioritizing improvement projects and enhancing road safety. The automated approach showcased in this research offers a promising avenue for strengthening roadside safety measures and preventing potential accidents. While acknowledging challenges such as periodic retraining and potential false positives, this approach stands as a promising addition to existing methods. The study culminates in a shapefile encompassing safety rankings, roadside features, and illustrative sample images, providing a tangible tool for UDOT in optimizing road safety strategies.

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EXECUTIVE SUMMARY

Recognizing the pivotal role of roadside hazards in rural crash occurrences and severity, this project aims to pinpoint the most perilous road segments based on FHWA safety rankings. The images collected by Mandli Communication Inc. serve as a valuable resource for vision-based evaluations. Mandli, specializing in data collection from U.S. highways through 3D pavement technology, mobile LiDAR, and geospatial technologies, provides comprehensive data for assessing safety parameters along each road segment. Before model training commenced, diverse preprocessing techniques were applied to the collected images, including color correction, resizing, and cropping. This research encompasses the development of various models to detect specific criteria on the roadside. Binary logistic regression models were developed for identifying guardrails on the roadside. Pretrained models were also established to detect the available clear zones, achieving an impressive accuracy of 83%. Additionally, a pretrained model was implemented for classifying images based on roadside slopes into three classes: low, mid, and high, demonstrating a commendable accuracy of 94% in identifying the correct class for roadside slopes.

Using the extracted features and developed algorithms, safety rankings were assigned to road segments on five state roads: US-6, SR-10, SR-12, US-40, and SR-150. The final product is a shapefile containing safety rankings and roadside features at specified intervals on these roads. This valuable resource empowers traffic engineers in the decision-making process, enabling them to prioritize projects that address problematic locations, such as removing overgrown trees and installing guardrails. Ultimately, this information contributes to improving road safety and averting potential crashes. The comprehensive nature of this project extends beyond conventional safety assessment methods. Utilizing machine learning algorithms and computer vision technologies establishes a robust framework for automating the evaluation of roadside conditions. The incorporation of various models addressing distinct criteria demonstrates versatility and precision in identifying potential hazards. Moreover, the project's focus on five state roads and the creation of a shapefile ensure a tangible and accessible output for transportation agencies, facilitating targeted interventions for enhanced safety. The success of this project relies on its ability to streamline the traditionally labor-intensive and time-consuming process of roadside safety assessment. By integrating cutting-edge technologies and data-driven approaches, it identifies hazardous locations and proposes a systematic method for prioritizing mitigation efforts. The collaboration with UDOT specialists ensures practical applicability and aligns the project outcomes with the objectives of transportation agencies.

In summary, this project pioneers an innovative approach to roadside safety assessment, offering a scalable model that can be adapted to diverse geographical settings. The combination of automated image analysis, machine learning, and collaboration with transportation authorities positions it as a transformative tool for proactively addressing roadside hazards and promoting safer roadways.

1. INTRODUCTION

1.1 Introduction

Roadway safety is a paramount concern in the United States, especially with the increasing number of fatalities in recent years. 2020 witnessed a troubling surge, with 38,824 lives lost in motor vehicle traffic crashes—a substantial 6.8% rise from the preceding year (Stewart, 2022). Among the critical contributors to these fatalities are roadway departures, instances where vehicles cross lane boundaries or exit the road, constituting approximately 50% of all traffic fatalities between 2016 and 2018. In Utah, despite accounting for only 15% of crashes, roadway departures are associated with over 40% of all fatalities (Utah SHSP, n.d.).

The challenges of roadway safety are particularly pronounced in rural areas, where factors such as higher average speeds, steeper embankments, hills, curves, and reduced lighting contribute to the prevalence of roadway departures. Figure 1.1 visually represents the primary crash categories for roadside departures in rural areas of the United States, underscoring the urgency of addressing safety concerns in these environments. Recognizing the critical role of the roadside condition in averting potential crashes or mitigating their severity, the Federal Highway Administration (FHWA) has introduced a rating system employing a seven-point categorical scale ranging from 1 (best) to 7 (worst).

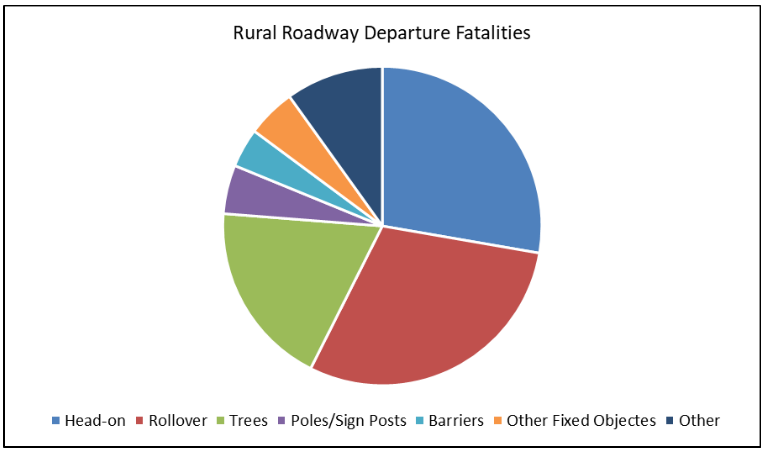

Figure 1.1 Rural Roadway Departure Fatalities Categories

Current efforts to address roadside safety conditions have primarily focused on specific factors, including guardrail detection, safety barrier type detection, and clear zones. While these endeavors mark essential strides, challenges persist in terms of accuracy, feasibility, and cost. The use of LiDAR and point cloud technology for evaluating factors like clear zones exemplifies attempts to enhance precision in assessment (Gouda et al., 2021). However, these approaches face limitations, hindering their widespread application. One notable drawback lies in the need for simultaneous consideration of all relevant criteria to comprehensively evaluate roadside safety conditions. Existing methods often lack the capability to holistically assess various factors concurrently, resulting in a fragmented understanding of the overall safety landscape. This limitation hampers the effectiveness of safety interventions and decision-making processes. In recognizing these challenges, there is a compelling need for an innovative and integrated approach that overcomes the shortcomings of current methods and provides a comprehensive evaluation of roadside safety conditions in rural areas. In response to these challenges, this research aims to introduce a transformative approach to roadside safety assessment in rural areas. The project seeks to develop an automated safety assessment system that comprehensively evaluates roadside conditions by leveraging advanced technologies such as computer vision, machine learning, and geospatial analysis.

The goal is to provide actionable insights to transportation agencies, enabling them to prioritize improvements and interventions that effectively enhance road safety and reduce the frequency and severity of crashes in rural settings.

1.2 Problem Statement

Identifying roadside features that threaten traffic safety is essential for all state departments of transportation (DOTs). This task is typically done by manually reviewing videos and images provided by third-party data providers, including companies like Mandli Communication Inc. However, this approach is time-consuming and prone to human error. Figure 1.2 presents an example image captured from I-80 at the 0.85-mile point.

Figure 1.2 A Sample Image from the Roadside of I-80

Computer vision has been pivotal in addressing numerous transportation-related challenges in recent years. Researchers have applied various algorithms, including convolutional neural networks (CNN) (Cross et al., 2020; Farhadmanesh, Marković, et al., 2022) and deep neural networks (DNN), to tackle issues such as pavement monitoring, vehicle detection, road safety, and asset management (Brilakis et al., 2011; Farhadmanesh et al., 2021a, 2021b; Farhadmanesh, Marković, et al., 2022; Farhadmanesh, Rashidi, et al., 2022; Matsumoto et al., 2021; Rashidi & Karan, 2018; Sherafat et al., 2022). The availability of extensive imagery and video data from Utah roads has further enabled the use of these algorithms to streamline the assessment of roadside features.

To address this, we have proposed developing an automated approach that harnesses computer vision and machine learning techniques to evaluate rural roadways based on various roadside safety criteria, such as side slopes, guardrails, and obstacles. This innovative approach aims to enhance the efficiency of assessing roadside safety without the need for additional hardware, relying solely on an imagery dataset. Multiple algorithms have been devised within this research to detect each specific roadside safety criterion. The culmination of this effort is a comprehensive map comprising road segments with safety rankings and detailed information about the safety conditions of each segment. Figure 1.3 illustrates an example of the final product.

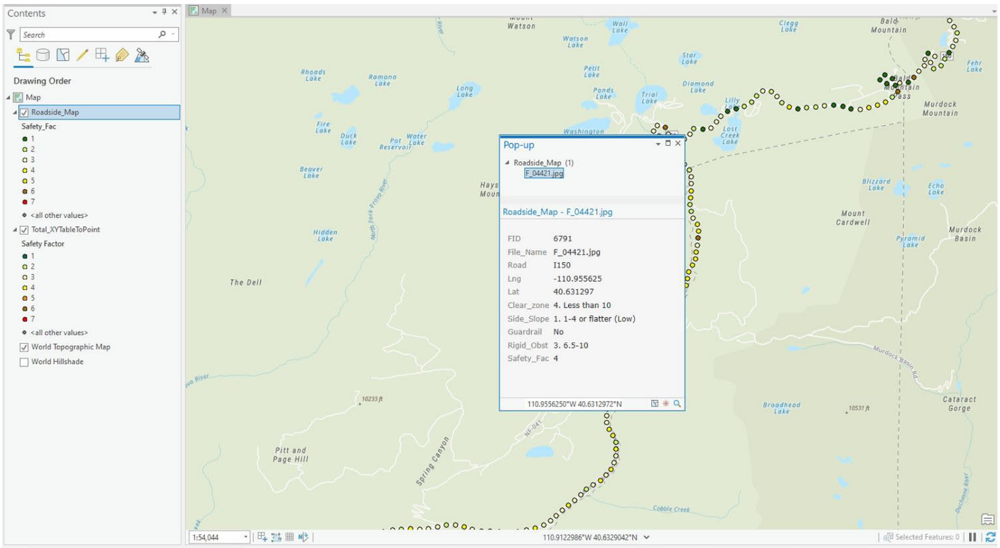

Figure 1.3 Final Product Including Safety Measurement at Road Segments

1.3 Objectives

This project has the primary goal of supporting the Utah Department of Transportation (UDOT) in screening rural roadways and subsequently prioritizing projects geared toward enhancing safety, such as removing trees and installing guardrails. The proposed methodology relies on machine learning algorithms and utilizes Mandli images as input data. The recommended criteria for assessing roadside safety align with the FHWA rating system, outlined in the following table:

Table 1.1 FHWA Rating of the Safety of the Roadside

Rating	Criteria
1	• Wide clear zones greater than or equal to 30 ft from the pavement edge line • Roadside slope flatter than 1:4 • Recoverable
2	• Clear zone between 20 and 25 ft from the pavement edge line • Roadside slope about 1:4 • Recoverable
3	• Clear zone about 10 ft from the pavement edge line • Roadside slope about 1:3 or 1:4 • Rough roadside surface • Marginally recoverable
4	• Clear zone between 5 to 10 ft from pavement edge line • Roadside slope about 1:3 or 1:4 • May have guardrails (5 to 6.5 ft from pavement edge line) May have exposed trees, poles, or other objects (about 10 ft from pavement edge line) • Marginally forgiving, but increased chance of a reportable roadside collision
5	• Clear zone between 5 to 10 ft from the pavement edge line • Roadside slope about 1:3 • May have guardrails (0 to 5 ft from pavement edge line) • May have rigid obstacles or embankments within 6.5 to 10 ft of the pavement edge line • Virtually non-recoverable.

6	• Clear zone less than or equal to 5 ft • Roadside slope about 1:2 • No guardrail • Exposed rigid obstacles within 0 to 6.5 ft of the pavement edge line • Non-recoverable
7	• Clear zone less than or equal to 5 ft • Roadside slope 1:2 or steeper • Cliff or vertical rock-cut • No guardrail • Non-recoverable with a high likelihood of severe injuries from roadside collisions

The proposed system comprises three distinct phases:

1. **Image Labeling:** This initial phase involves annotating and labeling images, a crucial step in preparing the dataset for subsequent model training.
2. **Model Training:** The research methodology section elaborates on detailed information regarding the model training process. This phase involves the utilization of machine learning algorithms to train models using the labeled imagery dataset.
3. **Application and Visualization:** The final phase focuses on the application and visualization of the developed models. This step is essential for translating the trained models into practical tools that can be applied to assess and prioritize safety improvements on rural roadways.

Readers are encouraged to refer to the research methodology section for comprehensive details on the model training process. More information about the final product's capabilities and outcomes can be found in the system evaluation section. The ultimate objective of this project is to provide valuable support to traffic engineers in their decision-making processes, aiding them in improving the safety levels of individual road segments.

1.4 Outline

- Introduction
- Background
- Methodology
- Data Collection
- Model Evaluation
- Conclusion

2. BACKGROUNDS

Understanding the factors influencing the safety performance of rural roadways is crucial for assessing their current status and pinpointing problematic segments. Key contributors to the safety risk on rural roads include the horizontal curve radius, longitudinal gradient, side slope grade, side slope height, distance between the roadway edge and fixed obstacles, the density of fixed obstacles (such as trees and utility poles), and the density of continuous fixed objects like substandard roadside safety barriers (Tang et al., 2019). The FHWA offers a safety rating for roadways, graded on a scale from 1 (best) to 7 (worst). The FHWA rating system encompasses factors such as clear zones, side slopes, and the presence of guardrails. Recognizing the significance of roadside conditions, numerous studies have explored the impact of roadside elements on the frequency and severity of crashes, with a summary of these findings presented in Table 2.1.

Table 2.1 Summarizing the Literature on the Effect of Roadside Elements on Road Crashes

Study	Approach	Findings
(Daniello & Gabler, 2011)	Exploratory data analysis	Collison with trees is 15 times more likely to be fatal than a collision with the ground
(Zou et al., 2014)	Binary logistic regression model	Find the risk of severity while hitting the guardrails; the risk of cable barrier was less than the rollover or hitting a pole or any fixed objects
(Manuel et al., 2014)	Negative binomial safety performance function for total collisions	Segment length, traffic volume, access-point density, and midblock changes were positively related, while the width is negatively related to collisions
(Roque et al., 2015)	Multinomial and mixed logit models using driver injury and severely injured occupant as the outcome variable	Critical slopes and horizontal curves without guardrail barriers significantly contributed to the run-off-roadway crashes
(J. Park & Abdel-Aty, 2015)	Naïve Bayes, generalized nonlinear models, multivariate adaptive regression spline	The number of crashes was reduced when the distance from the poles was increased
(Ewan et al., 2016)	Multivariate regression and correlation analysis	Roads with no shoulder have higher crash rates than roads with 4 to 5 feet shoulders.
(Haghighi et al., 2018)	Standard ordered logit model and multilevel order logit model (using hierarchical crash data) to evaluate the effect of roadway features on crash occurrence on a rural two-lane road	Lower risk of severe crashes in the presence of 10 ft-lane road, lower roadside hazards, higher driveway density, longer barrier length

As depicted in Table 2.1, there has been a notable increase in roadside safety studies in recent years. This surge may be attributed to the pivotal role of roadside elements in rural crashes and advancements in technology and data availability. Identifying locations lacking adequate safety measures is paramount for DOT initiatives. The prevailing approach relies on manual evaluation of roadside safety, a time-consuming and labor-intensive process. With the rapid evolution of computer vision algorithms, applying computer vision systems to enhance roadway safety becomes inevitable. Commonly utilized data for evaluating roadside safety include LiDAR data, 2D images, videos, and simulation-based analyses.

For example, Gao et al. (2020) employed mobile laser scanning to detect urban guardrails using density-based spatial clustering of applications with noise (DBSCAN) and multilevel filtering techniques. However, due to its straight-line fitting approach, this algorithm faces limitations in detecting curve guardrails. In another study, Zhong et al. (2019) utilized a point cloud-based classification method to detect roadside safety attributes and distances between them. While achieving higher precision in detecting poles and trees, this method had limitations in capturing a comprehensive number of objects compared with the ground truth. Rezapour & Ksaibati (2021a) adopted a CNN for roadside barrier detection, employing transfer and non-transfer learning. Transfer learning, derived from denseNet121, VGG19, and Inception v3 algorithms, exhibited varied accuracy rates—78%, 65%, and 97%, respectively. Only VGG19 surpassed non-transfer learning in accuracy, possibly due to the larger number of weights in its architecture, facilitating learning more complex features. Notably, non-transfer learning struggled to accurately detect the presence of box beams alone or in combination with guardrail configurations.

Given the crucial role of vegetation as a rigid obstacle on the roadside, several studies focused on its detection and classification. For instance, Harbaš et al. (2018) utilized convolutional networks for roadside vegetation detection. Similarly, Lau et al. (2015) employed a shallow neural network, a radial basis function neural network (RBFNN), comparing its performance with deep neural networks like convolutional neural networks in recognizing Malaysian traffic signs. Their CNN model achieved a recognition rate of 99% for traffic road signs, with incremental training demonstrating faster training compared with batch training. Table 2.2 provides a summary of some prominent CNN architectures.

From the literature review, it becomes evident that most previous studies concentrated on singular aspects of roadside safety parameters. Furthermore, the prevailing approach relies heavily on utilizing LiDAR data for classifying and detecting roadside safety concerns. While LiDAR data offer precision, it comes with significant expenses in data collection and processing. In light of these considerations, this project proposes a shift toward employing 2D images for the classification of roadside safety elements. The objective is to utilize a more cost-effective alternative that can effectively categorize and rank these elements based on the FHWA rating system.

Table 2.2 Summarizing Common CNN Architectures

Year	CNN Algorithm	Error Rate on ImageNet	No. of Parameters
2013	ZFNet	14.8%	-
2014	GoogLeNet	6.67%	4 million
2014	VGGNet	7.3%	138 million
2015	ResNet	3.6%	-
2015	Inception v3	4.2%	-
2018	NasNet	2.4%	3.2 million

3. METHODOLOGIES

Computer vision falls within the domain of machine learning, focusing on the automated interpretation, analysis, extraction, and comprehension of images and videos. These models are crafted to decipher visual data by recognizing features and contextual cues acquired during training. Subsequently, they apply these insights to interpret images and videos, facilitating predictive and decision-making tasks (*Deep Learning for Computer Vision*, n.d.) The spectrum of computer vision tasks can be broadly classified into three main groups:

1. **Image Classification:** Assigning labels to images from a set of predefined classes.
2. **Object Detection:** Identifying and pinpointing objects within an image or video.
3. **Image Segmentation:** Dividing an image into multiple parts or regions.

This section begins by delving into image preprocessing operations and exploring various image classification algorithms, including their respective advantages and disadvantages. Ultimately, the chosen algorithms for the image classification task will be detailed in Section 3.4.

3.1 Image Preprocessing

Preprocessing refers to a set of techniques and operations applied to raw data, particularly in the context of data analysis, machine learning, or signal processing, to transform and prepare it for further analysis or modeling. In the realm of image processing, preprocessing involves a series of steps aimed at enhancing, standardizing, or extracting relevant information from digital images before feeding them into algorithms or models. Common preprocessing steps include resizing images to a uniform size, normalizing pixel values for consistent scaling, cropping to focus on regions of interest, and applying augmentation to diversify the dataset. These techniques contribute to the overall quality, uniformity, and suitability of the data for subsequent tasks, such as image classification or object detection. Preprocessing is a crucial stage in the data pipeline, playing a key role in improving model performance, robustness, and interpretability.

3.1.1 Image Resizing

Image resizing is a fundamental preprocessing technique that involves adjusting the dimensions of an image. Resizing is essential for standardizing input sizes across a dataset, ensuring uniformity for machine learning models. It not only reduces computational complexity but also helps prevent model bias toward specific image sizes. During resizing, maintaining the aspect ratio is crucial to avoiding distortion and preserving the original content's proportions. This technique is particularly valuable when dealing with diverse image sources that may have varying resolutions.

3.1.2 Normalization

Normalization is the process of scaling pixel values in an image to a standard range, typically between 0 and 1. This technique aids in reducing the impact of varying intensity levels, enhancing model convergence during training. By normalizing pixel values, the model becomes less sensitive to differences in illumination or color variations, improving its ability to extract relevant features. Normalization is a common practice in image preprocessing, contributing to the stability and efficiency of machine learning models, especially neural networks.

3.1.3 Noise Removal

Noise removal is a fundamental step in image processing that involves the application of techniques to reduce or eliminate unwanted artifacts or disturbances from digital images. Image noise can manifest itself as random variations in pixel values, unwanted patterns, or distortions that degrade the quality and clarity of the image. Various noise removal methods aim to enhance the signal-to-noise ratio, making the images more suitable for analysis or interpretation. Common approaches include filtering techniques such as median filtering, which replaces each pixel value with the median value of its neighborhood, effectively smoothing out noise. Other methods involve the use of mathematical transforms or algorithms designed to identify and eliminate specific types of noise, such as Gaussian noise or salt-and-pepper noise. Noise removal is particularly crucial in applications such as medical imaging, where accurate and clear representations are essential for diagnostic purposes, or in computer vision tasks to ensure the reliability of feature extraction and object recognition. The goal of noise removal is to enhance the overall quality and fidelity of digital images, contributing to improved analysis and decision-making in various domains.

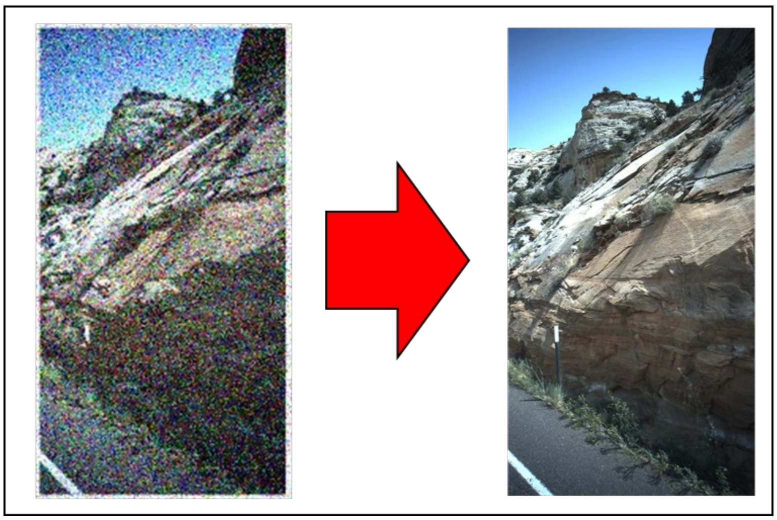

Figure 3.1 Noise Removal Results

3.2 Data Augmentation

Data augmentation is a machine learning and deep learning technique to expand the dataset's size by generating additional training data from existing samples. The specific augmentation methods applied vary based on the nature of the data being utilized. In image data, standard augmentation techniques involve flipping, rotating, scaling, and introducing noise or distortions to the images. By creating new training instances from the existing dataset, data augmentation mitigates overfitting—a common issue where a model excels on training data but falters on new, unseen data—and enhances the model's robustness. This process offers two key advantages: 1) generation of additional data, and 2) prevention of overfitting.

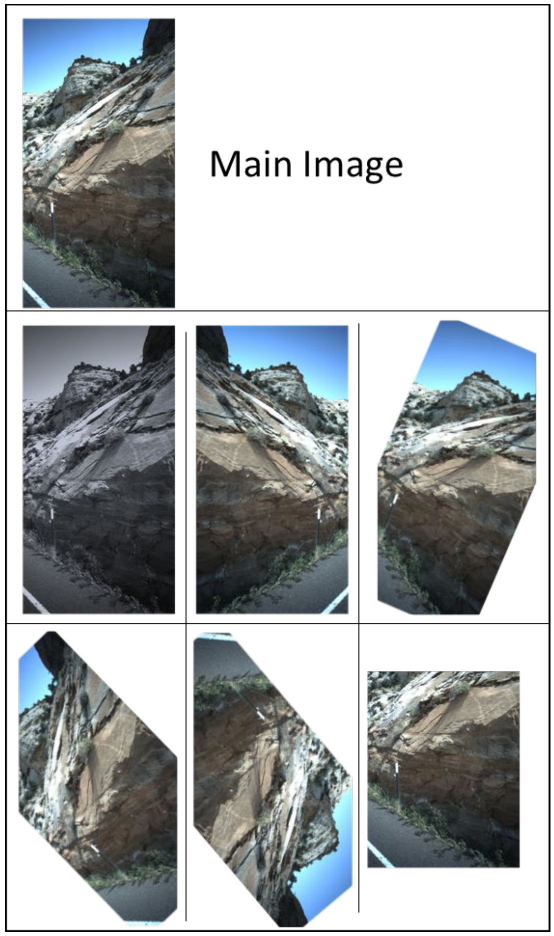

Figure 3.2 Sample Implementation of Data Augmentation

3.3 Image Classification Techniques

Classification involves labeling an image based on specific rules. The categorization rule may rely on one or more spectral or textural characterizations. Image classification techniques fall into two primary groups: unsupervised and supervised.

3.3.1 Unsupervised Classification

The unsupervised classification technique is a fully automated method that leverages machine learning algorithms to analyze and cluster unlabeled images. This process involves the identification of hidden image patterns without human intervention. Two widely used unsupervised classification techniques are K-means and ISODATA.

3.3.1.1 K-means

K-means is a clustering algorithm employed in unsupervised machine learning to partition a dataset into a predetermined number of clusters, considering the similarity among data points. The algorithm operates iteratively, assigning data points to the nearest cluster centroid and updating centroids based on the mean of the data points assigned to each cluster. Figure 3.3 illustrates clustering data points into three distinct groups.

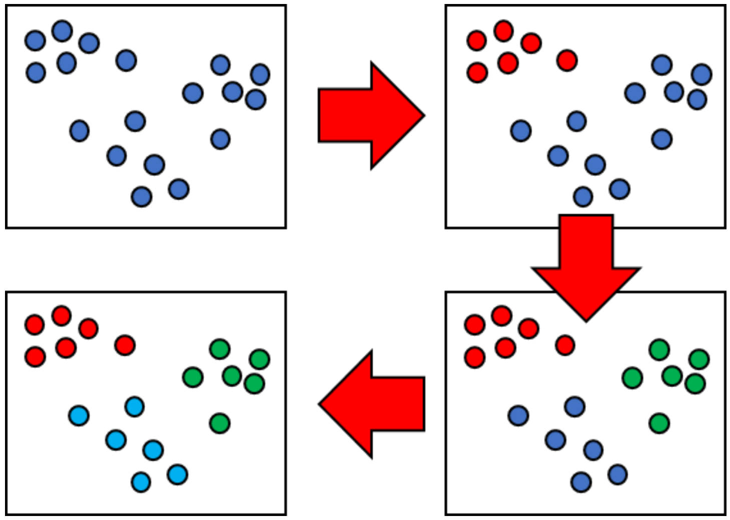

Figure 3.3 Data Points Clustering

3.3.1.2 ISODATA

The iterative self-organizing data analysis technique (ISODATA) is an unsupervised method employing Euclidean distance as the similarity measure to cluster data points into distinct classes. In contrast to K-means, the ISODATA algorithm does not assume the number of clusters beforehand and accommodates varying numbers of clusters. ISODATA boasts several advantages compared with other clustering algorithms. It excels in handling datasets with diverse cluster sizes and shapes, showcasing adaptability to changing cluster structures. However, it does come with limitations, including sensitivity to initial cluster assignments, and challenges in determining the optimal number of clusters for a given dataset.

3.3.2 Supervised Classification

In contrast to unsupervised classification, supervised classification methods require pre-labeled data (images) to train the classifier. In this approach, a portion of the dataset, known as the training set, is manually labeled and assigned to pre-selected categories, such as car, boat, bicycle, and bus. This labeling process facilitates model learning and establishes statistical measures applicable to the entire dataset. Subsequently, various image classifiers will be detailed in the following sections.

3.3.2.1 Support Vector Machine (SVM)

The support vector machine (SVM) is a supervised machine learning algorithm versatile in handling both classification and regression tasks. SVM minimizes the distance between the hyperplane and two or more data classes. Figure 3.4 depicts an instance of multiclass classification with SVM hyperplanes.

SVM is capable of handling both linear and nonlinear data by finding an optimal hyperplane or decision boundary that maximizes the margin between different classes or transforming data into a higher-dimensional space using the kernel trick (Mashhadi et al., 2021a, 2021b). The kernel function computes the dot product between data points in the elevated-dimensional space, enabling the algorithm to identify a hyperplane that separates data points, even when they are not linearly separable in the original feature space (Cheng et al., 2017; Mohammadi et al., 2023). SVM boasts several advantages over alternative classification algorithms, including its capability to handle high-dimensional data, resilience to outliers, and proficiency in managing nonlinear decision boundaries. However, SVM's sensitivity to the choice of kernel function and cost parameter and its computational demands for extensive datasets are considerations to bear in mind.

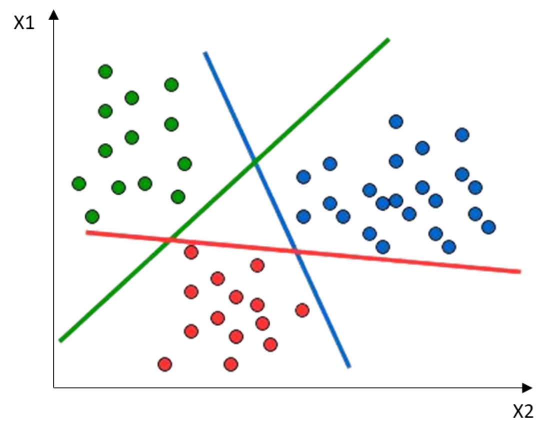

Figure 3.4 Multiclass Classification using SVM

3.3.2.2 Logistic Regression

Binary or binomial logistic regression is a supervised algorithm utilized for predicting the probability of a binary target variable. This method models the relationship between predictor features and the target variable by employing a linear function as an input to the logistic or sigmoid function. The logistic function, denoted by g(z), is defined as:

$$h_\theta(x) = g(\theta^T x) \text{ Where } 0 \leq h_\theta \leq 1 \tag{1}$$

where g is the logistic or sigmoid function which,

$$g(z) = \frac{1}{1 + e^{-z}} \; where \; z = \theta^T x \tag{2}$$

The sigmoid curve depicted in Figure 3.7 (left) illustrates the characteristic shape of the logistic function, with values constrained between 0 and 1. The assigned labels for each data point are determined based on the output probability. For instance, using a threshold of 0.5, the hypothesis function output is interpreted as positive if it is greater than 0.5; otherwise, it is considered negative. Figure 3.5 (right) visually represents a sample implementation of this interpretation. In addition to binomial logistic regression, two other categories exist:

1. **Multinomial:** This category is applicable when the target variable has three or more classes.
4. **Ordinal:** Ordinal logistic regression is suitable when the target variable consists of ordered categories, such as an application popularity ranking from 1 to 5.

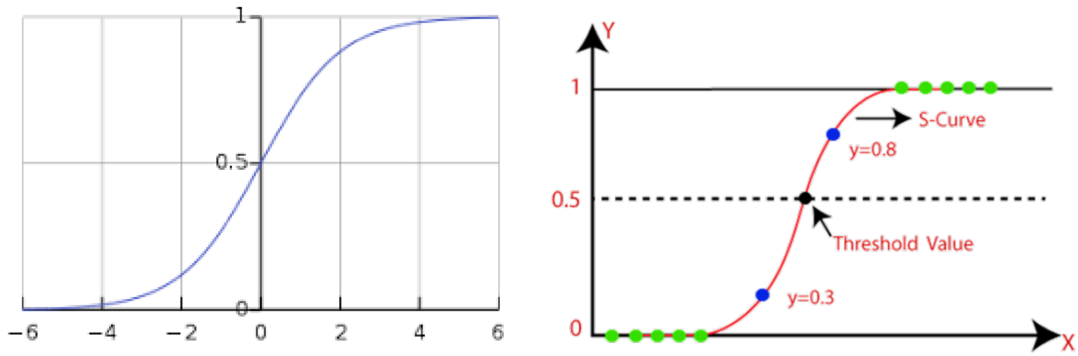

Figure 3.5 Left: Sigmoid Curve; Right: Sample Implementation of Logistic Regression Classification

3.3.2.3 Artificial Neural Networks (ANN)

An artificial neural network (ANN) consists of interconnected processing units known as nodes, functioning analogously to biological neurons. The model approximates the desired function by iteratively adjusting numerical connections between nodes, referred to as weights. The functional aspect of a neuron is illustrated in Figure 3.6.

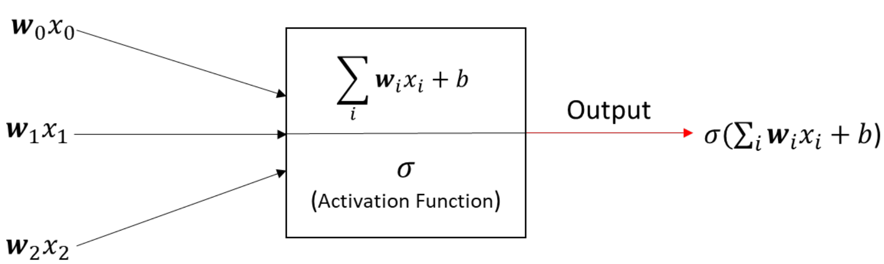

Figure 3.6 Nodes' Function in Neural Networks

The feedforward neural network is the most prevalent type of ANN, where data progresses from the input layer through one or more hidden layers to the output layer. Each neuron's output is determined by the activation function, considering the weighted sum of inputs. Figure 3.7 provides an example of a neural network architecture featuring two hidden layers. The number of neurons in these hidden layers can be adjusted to accommodate the level of approximation required. Notably, the number of neurons in the input and output layers must align with the dataset's dimension and the target attribute's number of classes, respectively.

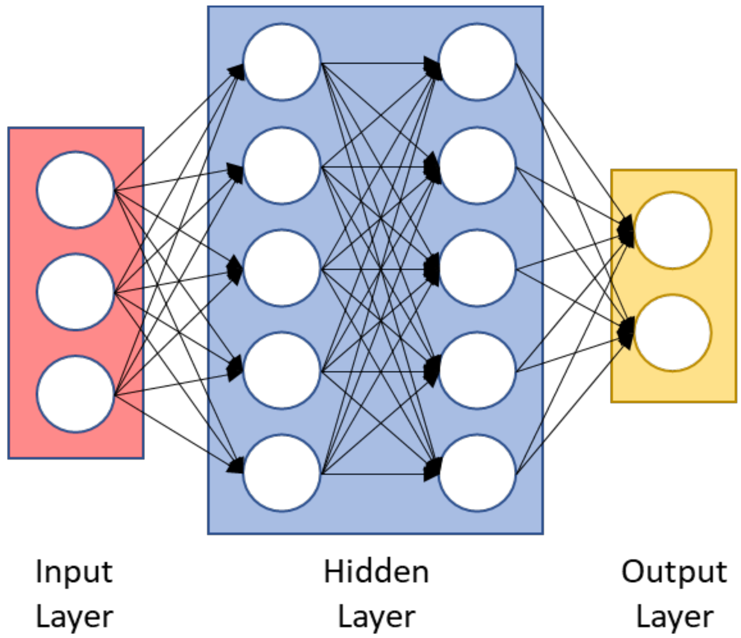

Figure 3.7 Neural Network Architecture

Hidden layers serve as discrete feature detectors aiding the model in pattern recognition. For instance, in recognizing a car, the initial hidden layer might detect lines, with subsequent layers progressively assembling these lines into a cohesive car structure. This hierarchical approach facilitates the recognition of complex objects. ANNs offer several advantages over traditional machine learning models, including their capability to handle intricate, nonlinear relationships in data and to learn from extensive datasets. However, they demand substantial computational resources and must be carefully regularized to mitigate the risk of overfitting.

3.3.2.4 Convolutional Neural Network (CNN)

The convolutional neural network (CNN) stands as one of the most widely employed deep learning algorithms, featuring two primary components:

1. Convolution layers: These layers focus on extracting features from input data, transforming it into a representative set of features (Yuan-Fu, 2019).
2. Classification layers: Responsible for determining the class of each input image based on the extracted features.

Feature extraction involves the conversion of input data (images) into a meaningful set of features, and the subsequent classifier layer utilizes these features to assign a class to each input. The robustness of CNNs has led to their application in diverse fields, including computer vision (Schneider et al., 2019; Xia et al., 2018), speech recognition (Pan et al., 2020; D. S. Park et al., 2019), and natural language processing (Alayba et al., 2018; Widiastuti, 2019). CNNs are comprised of multiple layers, including convolutional, activation, pooling, and fully connected layers. Figure 3.8 an example of CNN architecture for image classification. We will delve into the definition and function of each layer:

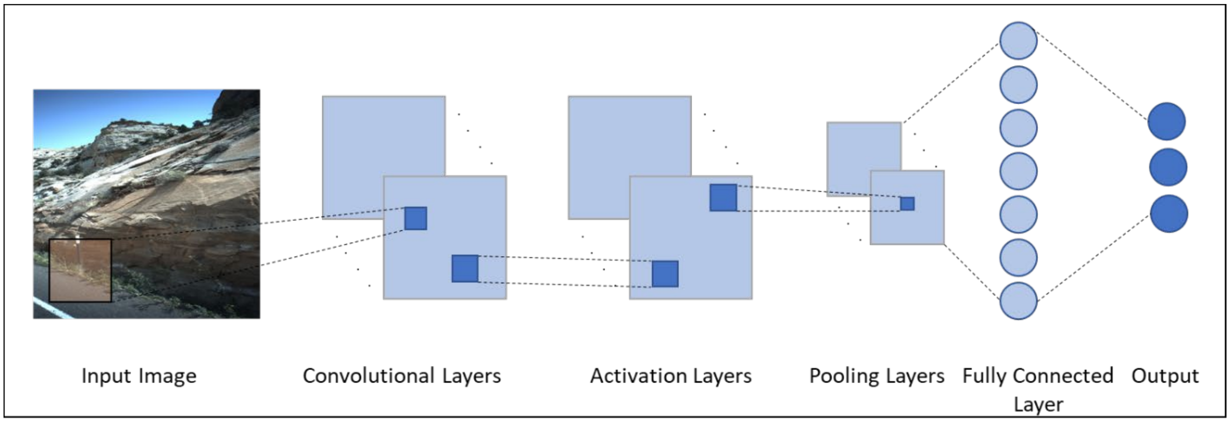

Figure 3.8 Sample Architecture of CNN

Convolutional layer: This crucial component incorporates multiple filters that convolve with the output of the previous layer, generating the output feature map. Figure 3.9 illustrates the calculation process at each step of the convolutional layers.

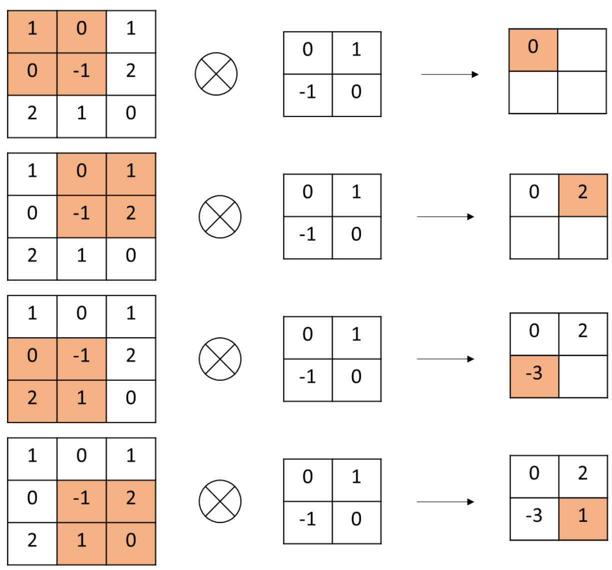

Figure 3.9 Convolution Calculation at Convolution Layers

Activation layer: Activation functions, such as sigmoid, tanh, rectified linear unit (ReLU), leaky ReLU, Maxout, and exponential linear units (ELU), introduce nonlinearity to the model, enabling the learning of complex relationships in the data. The choice of activation function depends on the specific task and network structure. Each activation function is defined mathematically.

Pooling layers: These layers aim to reduce feature matrices by partitioning input feature maps into non-overlapping regions and applying pooling functions (e.g., max pooling) to produce a single output value. Figure 3.10 illustrates the max pooling operation.

Figure 3.10 Max Pooling Operation

Fully connected layer: The final layer of a CNN is a fully connected neural network responsible for image classification based on features extracted from prior layers. Neurons in this layer are connected to all neurons from the previous and subsequent layers. Figure 3.11 presents an example of a fully connected neural network.

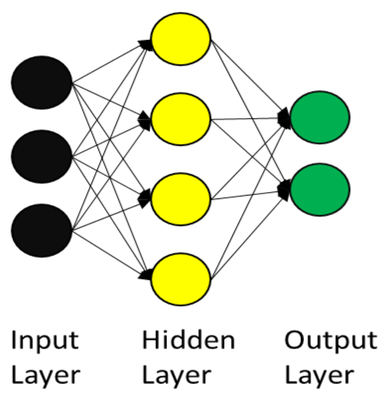

Figure 3.11 Fully Connected Neural Network Model

3.4 Algorithm Selection

This section delves into the algorithms selected for feature extraction and image classification. Despite the effectiveness of deep learning models, challenges such as limited data, prolonged training times, and high computational costs persist. To address these issues, transfer learning emerges as a valuable approach, involving repurposing a pretrained model as the foundation for constructing a new model on a different dataset (Mashhadi et al., 2023a, 2023b). Rather than starting from scratch, the weights of the pretrained model are leveraged for feature extraction, with only a few final layers being modified. Despite differences in the datasets between the project and the pretrained models, research has demonstrated that transferring features from remote datasets yields superior results compared with non-CNN models (Rezapour & Ksaibati, 2021). The subsequent sections provide a comprehensive overview of the algorithm chosen for feature extraction and image classification in this research.

3.4.1 Feature Extraction

Several pretrained models, including AlexNet, VGG16, VGG19, GoogleNet, and ResNet50, have undergone training on the extensive ImageNet dataset, comprising over 14 million images categorized into 1,000 classes (Deng et al., 2009). For the feature extraction step in this project, VGG16 is employed. The subsequent paragraphs provide an in-depth discussion of each method's architecture, advantages, and disadvantages.

Feature extraction plays a crucial role in image processing and computer vision tasks, converting raw input images into feature representations that encapsulate relevant information and characteristics essential for subsequent tasks like image classification, object detection, and segmentation. A practical approach for feature extraction involves utilizing models pretrained on extensive datasets, such as ImageNet, and fine-tuning them for specific applications. These pretrained models excel at extracting pertinent features from input images, which can then serve as inputs for other machine learning models. In this project, VGG16 is employed for feature extraction. Each model boasts a distinct architecture, offering various advantages and disadvantages. For example:

VGG16, designed by the Visual Graphics Group at Oxford, features 16 layers with small receptive fields and 3x3 convolutional filters. It follows a sequential structure with convolutional and max-pooling layers. VGG16 is known for its simplicity and uniform architecture, making it easy to understand and implement. It performs well in capturing intricate patterns. The depth of the network can lead to high computational costs and memory requirements during training.

Figure 3.12 VGG16 Architecture (Top 4 Pretrained Models, n.d.)

3.4.2 Image Classification

Following feature extraction, the subsequent step in image classification involves utilizing an algorithm to classify the extracted features from the images. A CNN model typically comprises convolutional layers and a fully connected neural network. To enhance the precision of the model, this project proposes a combination of CNN and eXtreme gradient boosting (XGBoost), a robust classification algorithm. The architecture of the suggested method is depicted in Figure 3.13. The following paragraphs provide further details about the XGBoost algorithm.

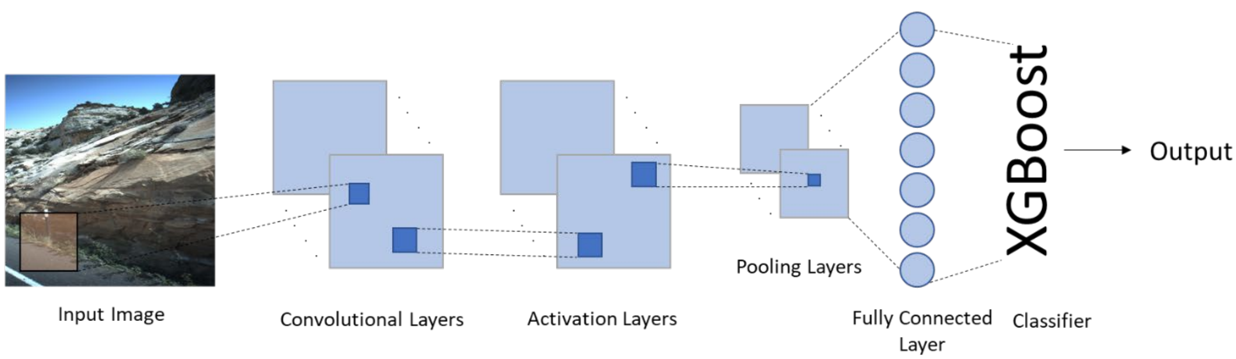

Figure 3.13 Combining CNN and XGBoost Algorithms

3.4.2.1 XGBoost

XGBoost is a supervised learning algorithm rooted in the gradient-boosting decision tree (GBDT) framework. GBDT is an ensemble learning algorithm, similar to a random forest, applicable for both classification and regression tasks. The key similarity between GBDT and random forest lies in their composition of multiple decision trees. However, the method of building these trees differs between the two approaches. In a random forest, the bagging technique is employed to build full trees independently.

On the other hand, GBDT adopts an iterative approach to train an ensemble of shallow decision trees. The boosting ensemble technique encompasses three fundamental steps:

- Initial model (F_0): An initial model, denoted as F_0, is defined to predict the target variable y.
- Residual calculation: This initial model is associated with the residual (y – F_0), representing the difference between the actual values and the predictions made by F_0.
- New model (h_1) fitting to residuals: A new model, denoted as h_1, is fitted to these residuals, capturing the errors or misclassifications made by the initial model.
- Boosted model (F_1): The boosted version of F_0, denoted as F_1, is obtained by combining F_0 and h_1. This combination results in F_1 having a lower mean squared error than F_0, signifying an improvement in predictive accuracy.

In order to classify images based on roadside safety factors, various computer vision algorithms have been developed using logistic regression, pretrained CNN models, and XGBoost. Figure 3.15 depicts the process of image classification using the suggested approach. The next section discusses the process of data collection.

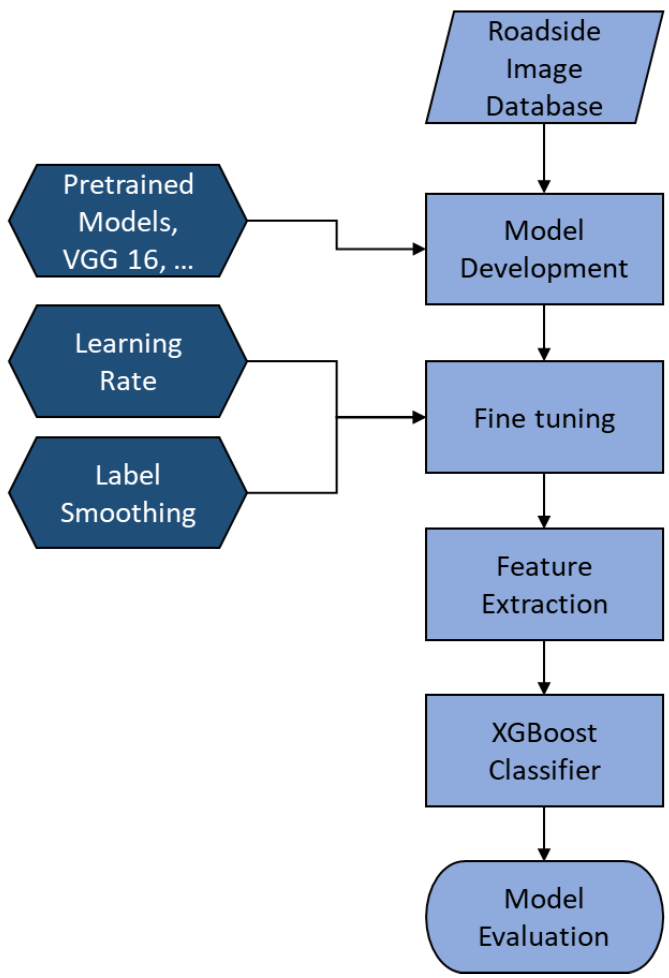

Figure 3.14 Flowchart of the Selected Approach

4. DATA COLLECTION

UDOT (Utah Department of Transportation) implements a comprehensive data collection plan, regularly obtaining road and roadside imagery along with LiDAR data. This dataset serves various purposes, including road safety analysis, traffic management, and infrastructure planning. Mandli Communication Inc. conducts the data collection at least biennially, ensuring a consistently updated dataset for UDOT's use. The approach involves capturing high-resolution images of the entire state road network, encompassing urban and rural areas. The data collection process entails the use of specialized cameras mounted on vehicles assigned to designated routes. These cameras capture both forward- and backward-facing images, providing an extensive view of the road and its surroundings. Simultaneously, LiDAR data are collected using laser scanning technology to measure distances between the vehicle and ground objects.

Mandli Communication Inc. employs 3D pavement technology, mobile LiDAR, and geospatial technologies for data collection on U.S. highways. The collected data facilitates the evaluation of safety parameters along each road segment in Utah. Figure 4.1 showcases one of the vehicles utilized by Mandli for data collection, equipped with various instruments.

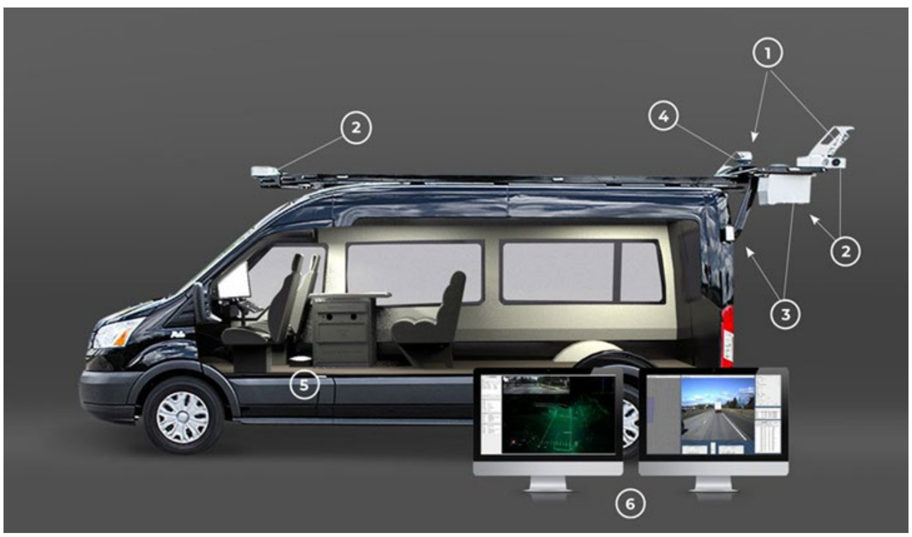

Figure 4.1 Mandli Vehicle Used for Data Collection

1. Dual Velodyne HDL-32 LiDAR sensors.
2. Nine 8.9 MP cameras delivering 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 (Mandli X-35 - Mandli Communications, n.d.).

The front-facing cameras on the vehicle capture different angles of the roads, as illustrated in Figures 4.2-4.4:

Figure 4.2 A Sample View of Mandli Images from SR-10 at Mileage 50 (Year 2019)

Figure 4.3 A Sample View of Mandli Images from SR-10 at Mileage 50 (Year 2020)

Figure 4.4 A Sample View of Mandli Images from SR-10 at Mileage 50 (Year 2021)

To encompass diverse conditions, the dataset was systematically collected from various roads and mileages. The proposed approach strategically leverages specifically selected images captured in 2020 from the right-hand side to assess the roadside conditions of each road segment (referring to the right portion in Figure 4.3). A more comprehensive assessment of the roadside situation is achieved by concentrating on the right-hand side images, facilitating a more accurate and thorough evaluation process. Figure 4.5 illustrates different situations at distinct road segments, showcasing the varied conditions considered in the dataset analysis.

Figure 4.5 Various Roadside Conditions on Utah's Roads

5. MODEL EVALUATION

The Federal Highway Administration (FHWA) has proposed a comprehensive seven-point categorical scale ranging from 1 (best) to 7 (worst) to evaluate roadside safety, as outlined in Table 1.1. This scale considers various factors crucial for assessing safety along roadways. Four major road parameters significantly contribute to roadside safety, including the presence of a clear zone, the existence of guardrails, the roadside slope characteristics, and the identification of rigid obstacles such as trees, embankments, and rocks. To furnish the Utah Department of Transportation (UDOT) with in-depth insights into safety criteria for each road segment, distinct models have been developed for each of these parameters. In the subsequent sections, the outcomes of each model will be presented, shedding light on the safety conditions related to clear zones, guardrails, roadside slopes, and rigid obstacles along different road segments.

5.1 Guardrail Detection

Guardrail detection is a critical component of roadside safety assessment, aiming to identify the presence and condition of guardrails along road segments. Guardrails play a pivotal role in preventing vehicles from leaving the roadway and mitigating the severity of potential accidents. A dedicated model has been developed for guardrail detection in the context of the proposed method for evaluating roadside safety. Leveraging computer vision algorithms and machine learning techniques, this model analyzes images captured by Mandli Communication Inc. to identify and assess the condition of guardrails. The accuracy of the guardrail detection model, reaching 93%, underscores its effectiveness in automatically recognizing these safety features. The outcomes of this model provide valuable information to UDOT, contributing to the overall safety ranking of road segments and assisting in prioritizing projects to improve guardrail conditions where needed. Guardrail detection is a crucial aspect of the comprehensive approach to roadside safety evaluation, enhancing the capability to address specific parameters and contributing to transportation departments' overall safety enhancement efforts.

A binary logistic regression model has been meticulously developed to identify guardrails on the roadside. This model utilizes a binary classification approach, distinguishing between road segments with and without guardrails. Figure 5.1 visually presents two sample images captured from Utah roadways, showcasing the application of the guardrail detection model. The logistic regression model operates based on the learned relationships between input features extracted from the images and the binary outcome of the presence or absence of guardrails. The proposed method can effectively categorize road segments by employing this model, providing valuable insights into guardrail conditions. The binary logistic regression model contributes to the overall safety assessment, offering a specific and detailed evaluation of guardrail presence along different road segments, which is crucial for enhancing roadway safety and guiding targeted improvement initiatives.

Figure 5.1 Roadside View for Detecting Guardrails

5.2 Rigid Obstacle Detection

Rigid obstacles, encompassing elements such as trees, embankments, and rocks, pose significant challenges to roadside safety. Identification and assessment of these obstacles are crucial for implementing targeted safety measures and infrastructure improvements. A dedicated model for rigid obstacle detection has been developed in the context of the proposed methodology. This model utilizes machine learning techniques, including logistic regression and integration with other relevant models, to automatically identify and evaluate the presence of rigid obstacles along road segments. The integration of models has proven effective, yielding an impressive accuracy of 94%. The outcomes provide valuable insights into the roadside conditions, enabling transportation departments like UDOT to prioritize projects to address specific rigid obstacles and enhance overall roadway safety.

Figure 5.3 depicts the confusion matrix for rigid obstacle detection. In the context of evaluating the performance of a multiclass classification model, a confusion matrix serves as a fundamental tool. The structure of the multiclass confusion matrix involves rows and columns representing predicted and true labels, respectively. Each cell within the matrix signifies the percentage of instances predicted to belong to a specific class but actually belong to another class. Crucially, the diagonal cells along the matrix indicate the percentage of instances that have been correctly classified for each class. This comprehensive assessment allows for a detailed understanding of how well the model performs across different classes, providing insights into accuracy and potential misclassifications. The multi-class confusion matrix is a valuable metric for validating the effectiveness of the developed models, offering a quantitative perspective on their ability to accurately classify instances within various categories.

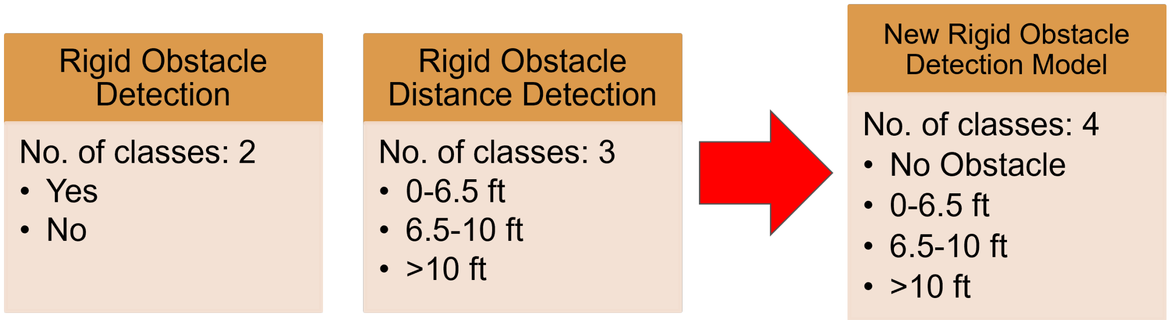

Figure 5.2 Rigid Obstacle Model Integration

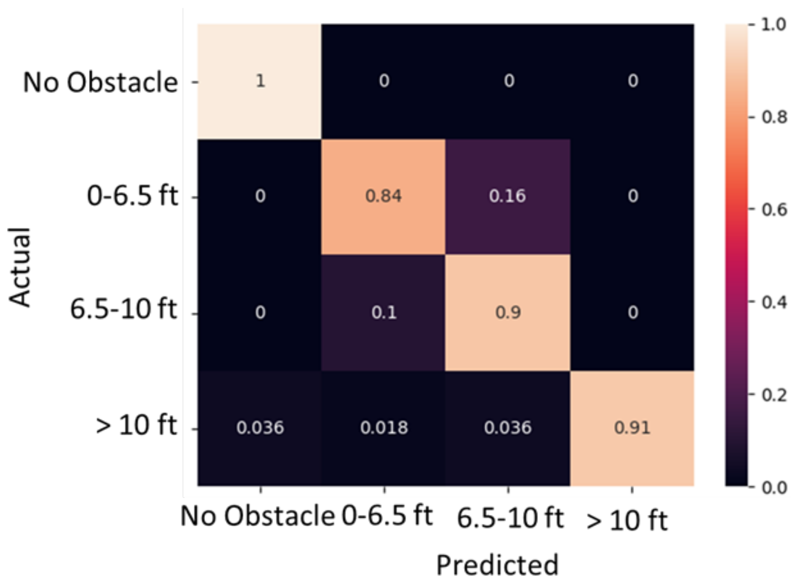

Figure 5.3 Confusion Matrix for Rigid Obstacle Detection

5.3 Clear Zone Detection

Figure 5.4 serves as an illustrative guide defining the clear zone in accordance with the guidelines outlined in the Roadside Design Guide Manual. The clear zone, a critical parameter in assessing roadside safety, refers to a designated area alongside a roadway that should ideally be free of obstacles or hazards. As depicted in the figure, the clear zone extends from the edge of the travel lane to a specified distance, aiming to provide a buffer zone that minimizes the potential for collisions and enhances overall safety.

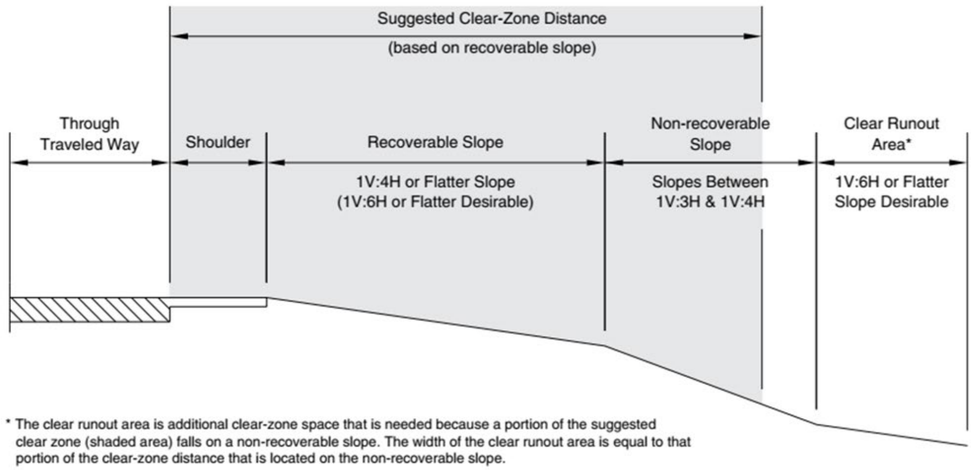

Figure 5.4 Clear Zone Definition Based on Roadside Design Guide
(AASHTO Roadside Design Guide, n.d.)

Table 5.1 delineates the clear zone intervals, showcasing a modification from the FHWA standards based on the approvals of UDOT engineers. Recognizing certain gaps in the existing clear zone intervals, UDOT engineers have proposed adjustments to better align with safety considerations and specific road conditions. The table serves as a comparative reference, presenting both the original FHWA and the suggested intervals and clarifying the approved adjustments. This collaborative effort between UDOT engineers and FHWA standards aims to tailor clear zone intervals to the unique characteristics of Utah roadways, ensuring a more effective and context-specific approach to roadside safety evaluation.

Table 5.1 FHWA Intervals for Clear Zone and the Suggested Intervals

Class	FHWA Intervals	Suggested Intervals
1	Greater than 30 ft	Greater than 30 ft
2	20-25 ft	20-30 ft
3	About 10 ft	10-20 ft
4	5-10 ft	5-10 ft
5	Less than 5 ft	Less than 5

The utilization of VGG16 in conjunction with XGBoost has yielded promising results, demonstrating an 83% accuracy in correctly identifying the class for roadside slopes. The confusion matrix, depicted in Figure 5.5, provides a visual representation of the model's performance in terms of classifying instances into different slope categories. A confusion matrix is a valuable tool for assessing the strengths and potential shortcomings of the model, offering insights into the distribution of correct and misclassified instances across the various slope classes. The collaborative approach involving VGG16 and XGBoost enhances the overall capability of the model to accurately classify roadside slopes, contributing to the comprehensive safety evaluation of road segments. These findings underscore the effectiveness of combining deep learning and gradient boosting techniques for improved accuracy in detecting and classifying specific roadside features.

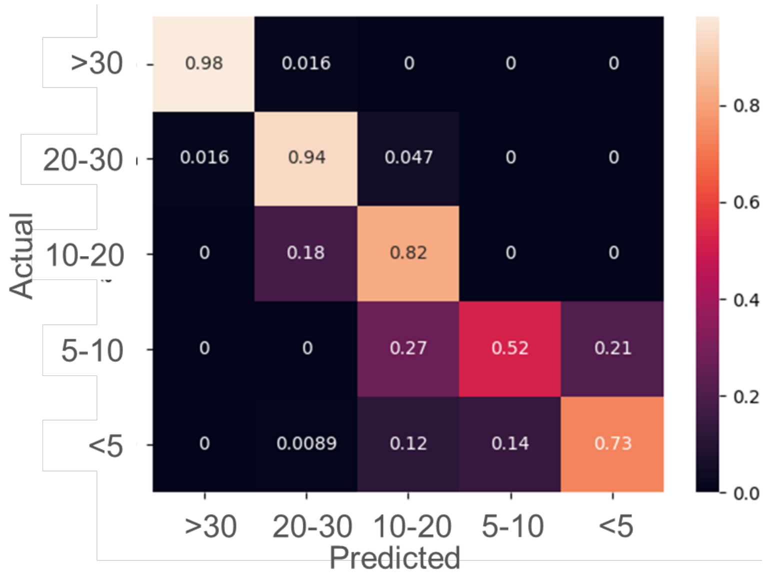

Figure 5.5 Confusion Matrix for Clear Zone Detection

5.4 Roadside Slope Detection

The Roadside Design Guide emphasizes the significance of evaluating roadside slopes, particularly beyond the shoulder area, as highlighted in Figure 5.6. Recognizing the critical role of roadside slopes in safety considerations, this guide provides essential guidelines for assessing and designing roadways to ensure optimal conditions. Furthermore, the MIRE (Model Inventory of Roadway Elements) guidelines offer specific insights, stating that side slopes may not be applicable to roads when roadside barriers are present. This underscores the nuanced approach required in safety assessments, acknowledging the influence of various factors, including the presence of barriers. By aligning with established guides such as the Roadside Design Guide and MIRE, road safety evaluations can effectively account for and address the complexities associated with roadside slopes and their interaction with other safety elements.

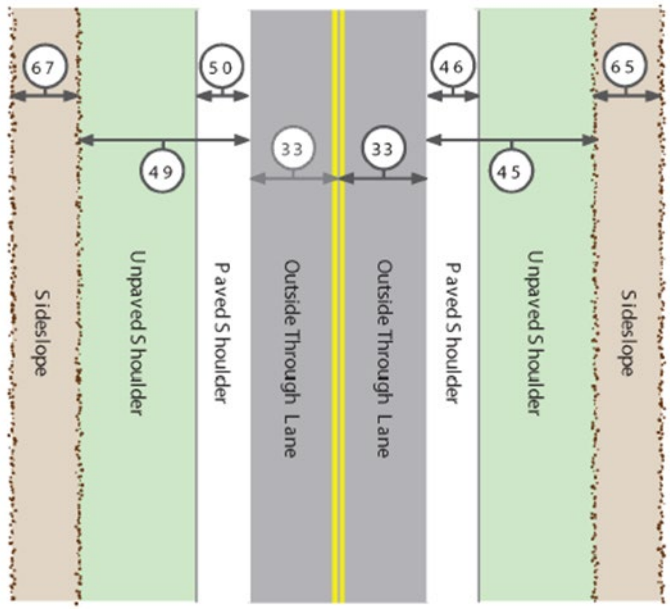

Figure 5.6 Illustration of Cross Section, Two-Lane Roadway

The FHWA rating system encompasses six specific categories related to side slope, each defined by the degree of slope expressed as a ratio. These categories range from side slopes flatter than 1:4 to side slopes of 1:2 or steeper. Recognizing the complexity of detecting and classifying slopes solely through 2D images, a simplification strategy has been implemented. The classification process has been streamlined into low, med, and high categories, as illustrated in Figure 5.7. This simplification facilitates a more straightforward analysis by grouping similar slope characteristics, and it also aligns with the differentiation of ratings based on the examination of available clear zone ranges. This approach enhances the practicality of assessing and categorizing side slopes, contributing to a more effective and interpretable roadside safety evaluation.

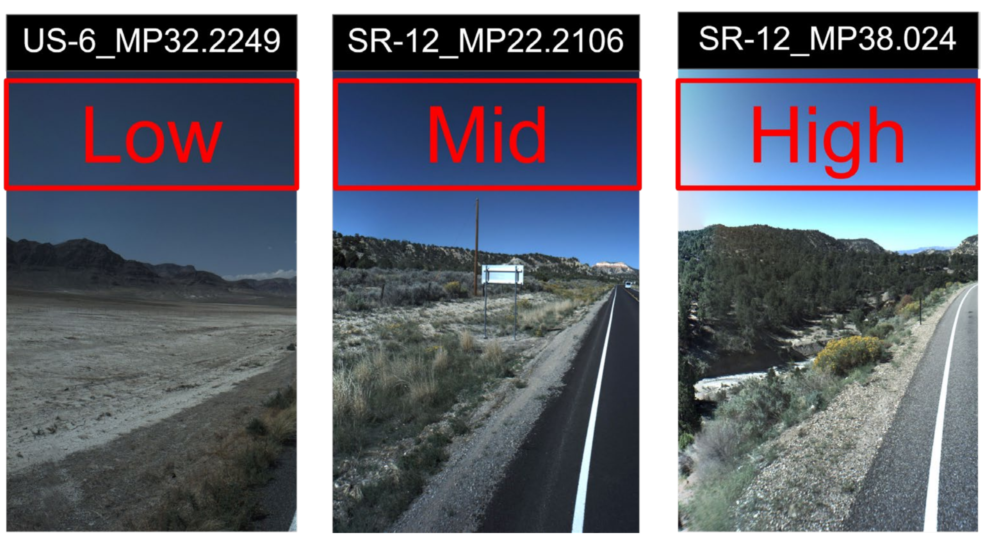

Figure 5.7 Sample Images for Roadside Slope Categorization

Based on the results, the developed model yielded significant results in categorizing images into three groups (Figure 5.8).

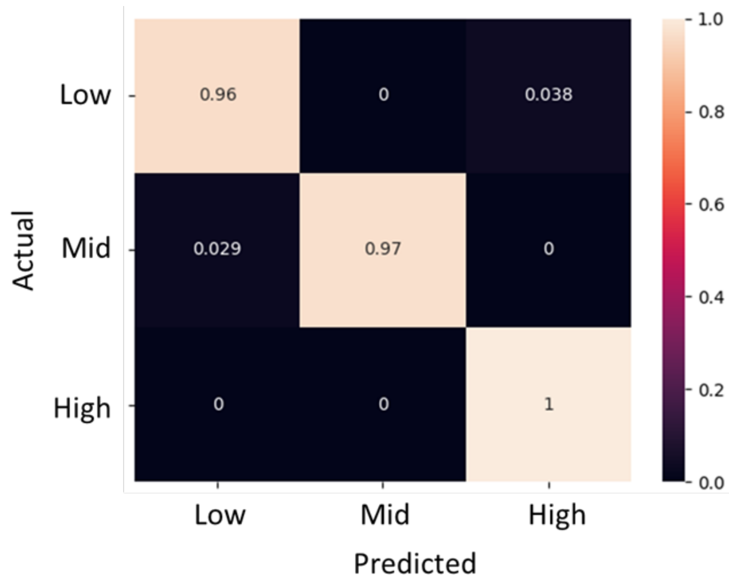

Figure 5.8 Confusion Matrix for Roadside Slope Detection

5.5 Safety Ranking

Following the extraction of features from the roadside, a collaborative effort between the research team and UDOT specialists resulted in the development of an algorithm designed to evaluate and rate roadside conditions. This algorithm relies on utilizing four key features extracted through computer vision algorithms: guardrails, clear zones, rigid obstacles, and roadside slopes. Through the incorporation of these features, the algorithm systematically calculates a rating for each road segment. The implementation of this rating system serves as a valuable tool for UDOT, providing a means to monitor and assess the condition of roadway peripheries. Moreover, the generated ratings enable UDOT to strategically prioritize maintenance and repair efforts based on objective, data-driven metrics. By adopting such an approach, UDOT can optimize the allocation of resources, ensuring an effective and efficient enhancement of roadside safety.

Algorithm 1 Roadside Safety Ranking

If Guardrail = yes **THEN**
    If 6.5 ft ≤ Rigid Obstacle ≤ 10 ft **THEN** Rating = 5
    ELSE Rating = 4
ELSEIF Clear Zone ≤ 5 ft **AND** Roadside Slope = High **THEN** Rating = 7
ELSEIF Clear Zone ≤ 5 ft **AND** Rigid Obstacle ≤ 6.5 ft **THEN** Rating = 7
ELSEIF Roadside Slope = High **AND** Rigid Obstacle ≤ 6.5 ft **THEN** Rating = 7
ELSEIF Clear Zone ≤ 5 ft **OR** Roadside Slope = High **OR** Rigid Obstacle ≤ 6.5 ft **THEN** Rating = 6
ELSEIF 6.5 ft ≤ Rigid Obstacle ≤ 10 ft **THEN** Rating = 5
ELSEIF Rigid Obstacle ≥ 10 ft **OR** 5 ft ≤ Clear Zone ≤ 10 ft **THEN** Rating = 4
ELSEIF 10 ft ≤ Clear zone ≤ 20 ft **OR** Roadside Slope = Mid **THEN** Rating = 3
ELSEIF 20 ft ≤ Clear zone ≤ 30 ft **THEN** Rating = 2
ELSEIF Clear zone ≥ 30 ft **THEN** Rating = 1

5.6 Final Product

The ultimate output of this project is a shapefile that encompasses critical information such as image ID, road name, latitude, longitude, safety ranking, and roadside features for each designated road segment. Specifically, the data are compiled for five state roads: US-6, SR-10, SR-12, US-40, and SR-150. This comprehensive shapefile is a repository for valuable insights derived from assessing roadside conditions. It includes essential details for UDOT's decision-making processes, offering a holistic view of safety rankings and associated features along the specified roadways. Including sample images further enhances the utility of the shapefile, providing visual context to support informed decision-making by UDOT authorities.

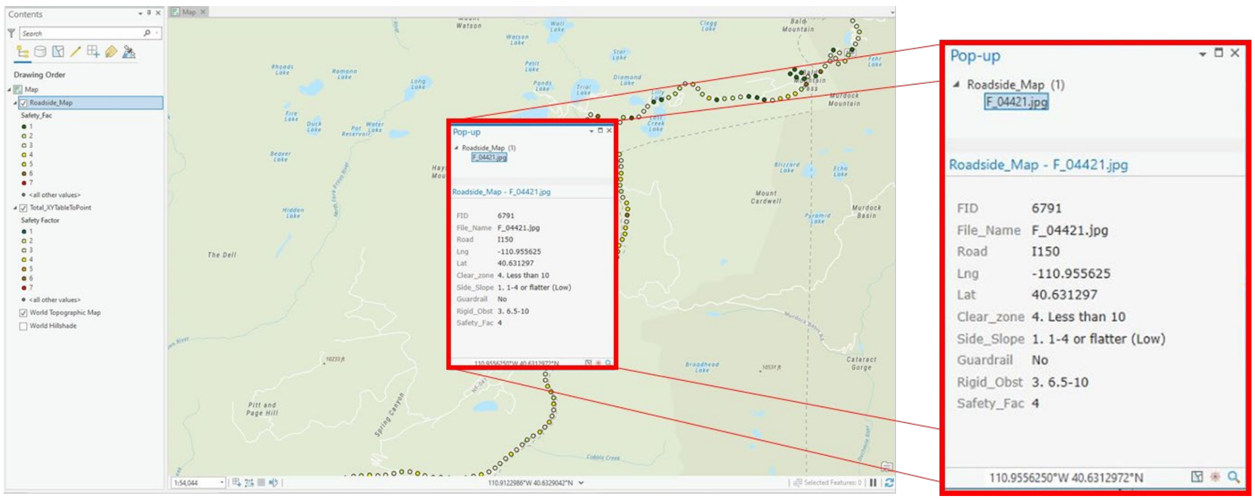

Figure 5.9 Precited Conditions of the Roadside (#1)

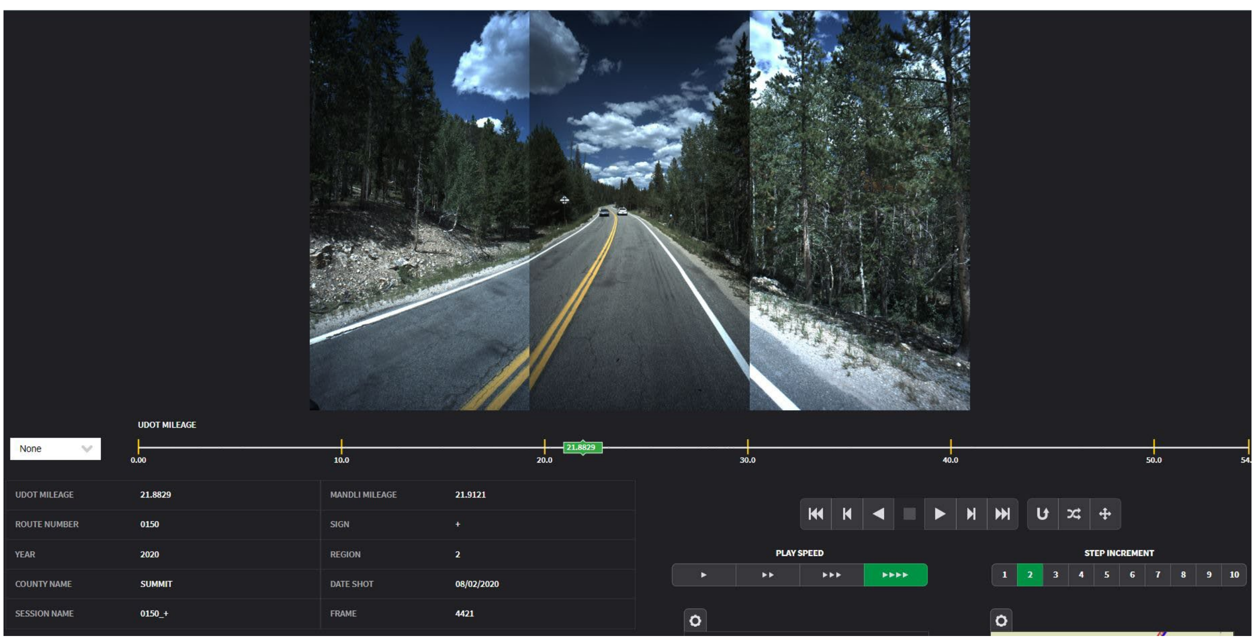

Figure 5.10 Actual Condition of the Point Listed in the Previous Figure (#1)

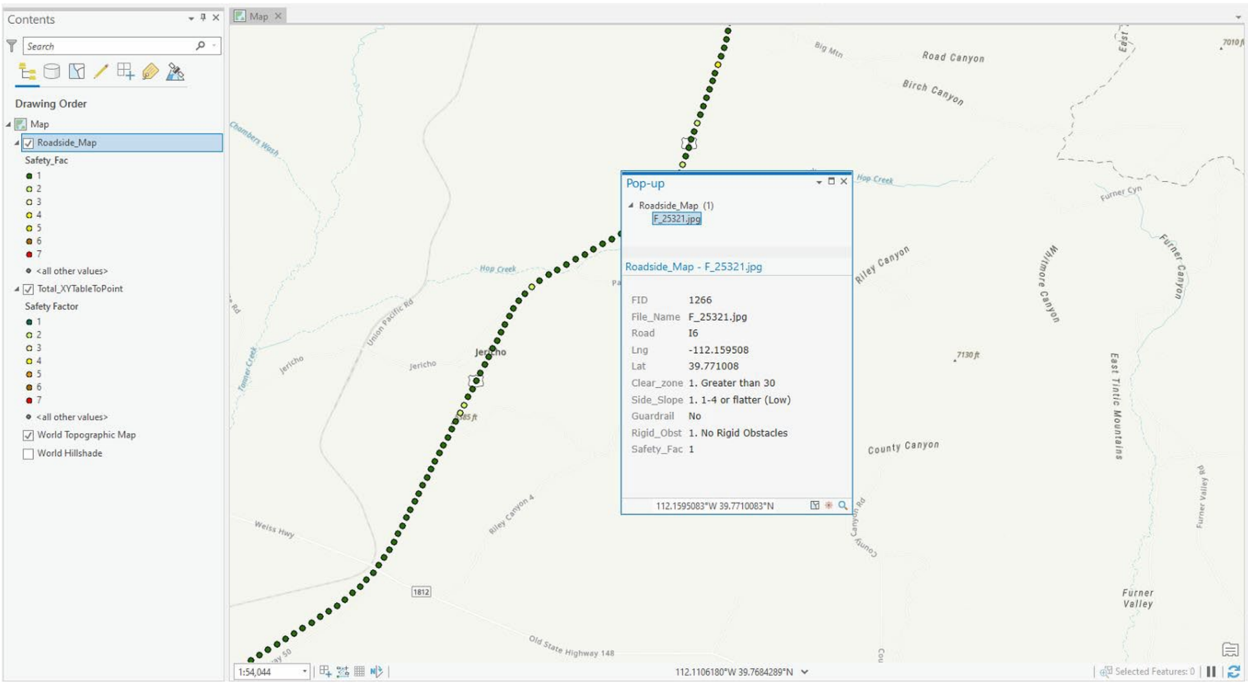

Figure 5.11 Precited Conditions of the Roadside (#2)

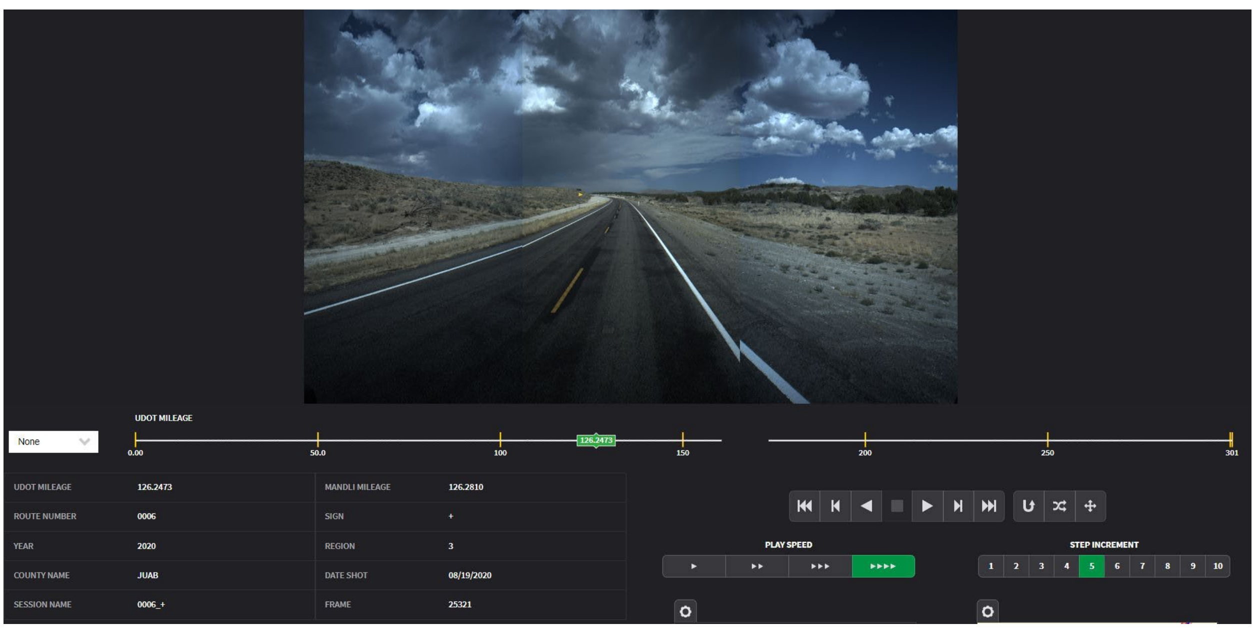

Figure 5.12 Actual Condition of the Point Listed in the Previous Figure (#2)

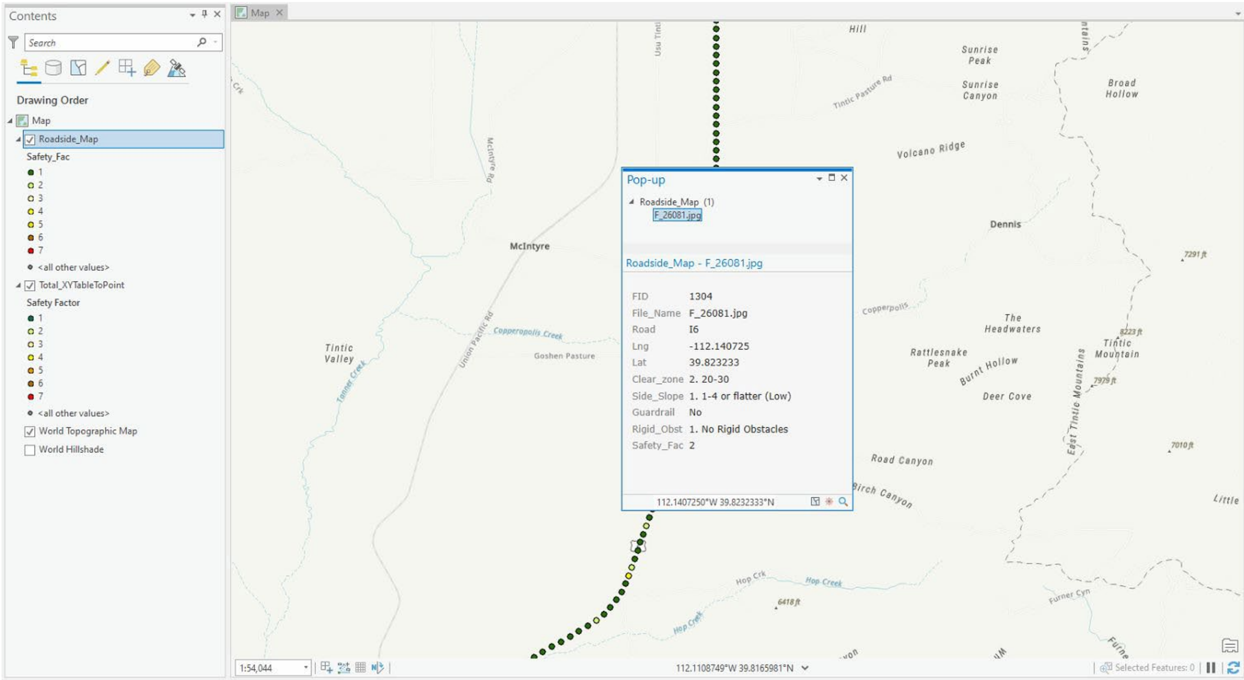

Figure 5.13 Precited Conditions of the Roadside (#3)

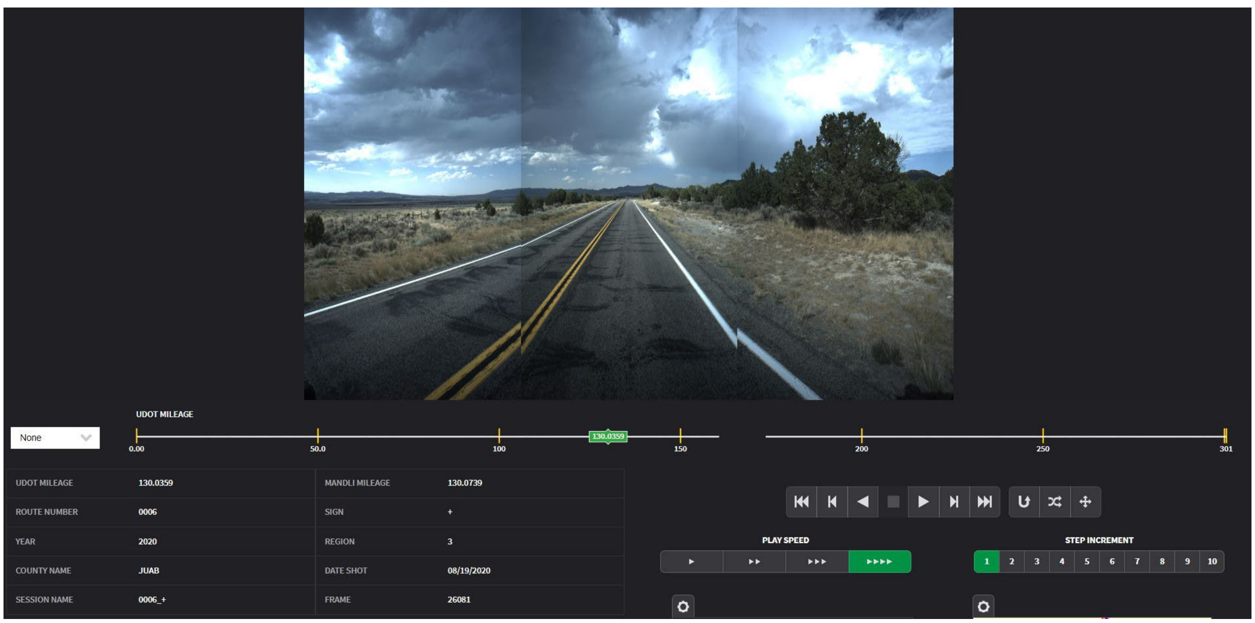

Figure 5.14 Actual Condition of the Point Listed in the Previous Figure (#3)

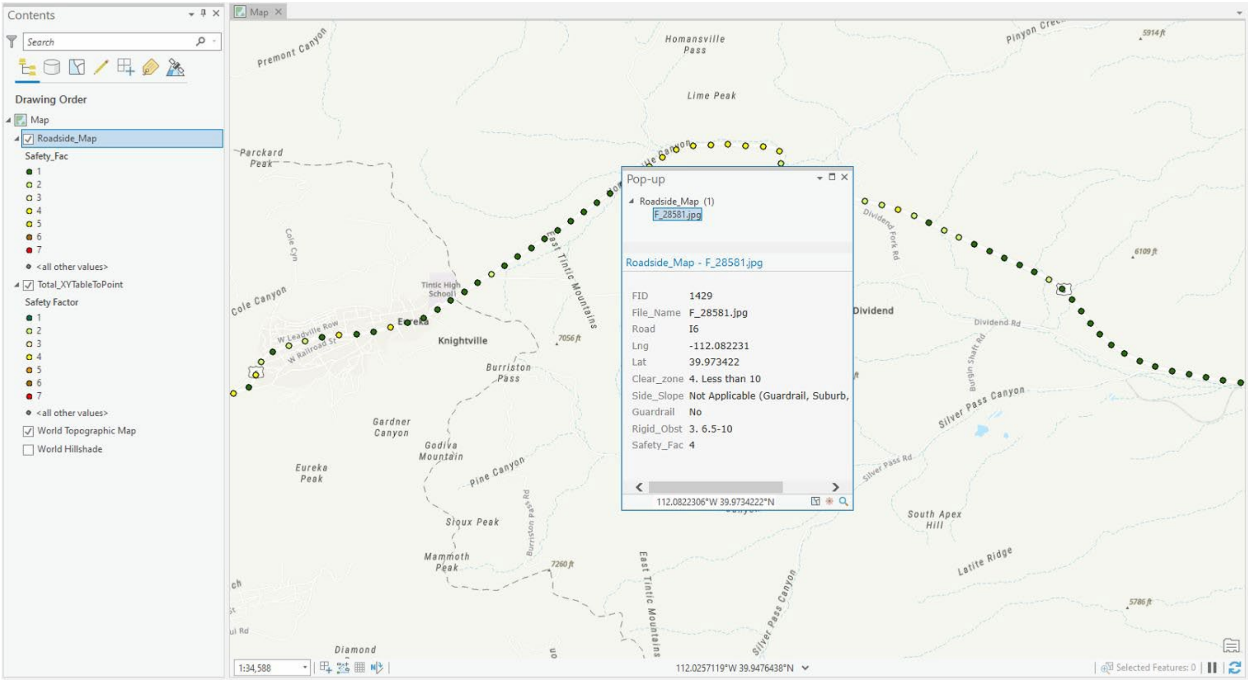

Figure 5.15 Precited Conditions of the Roadside (#4)

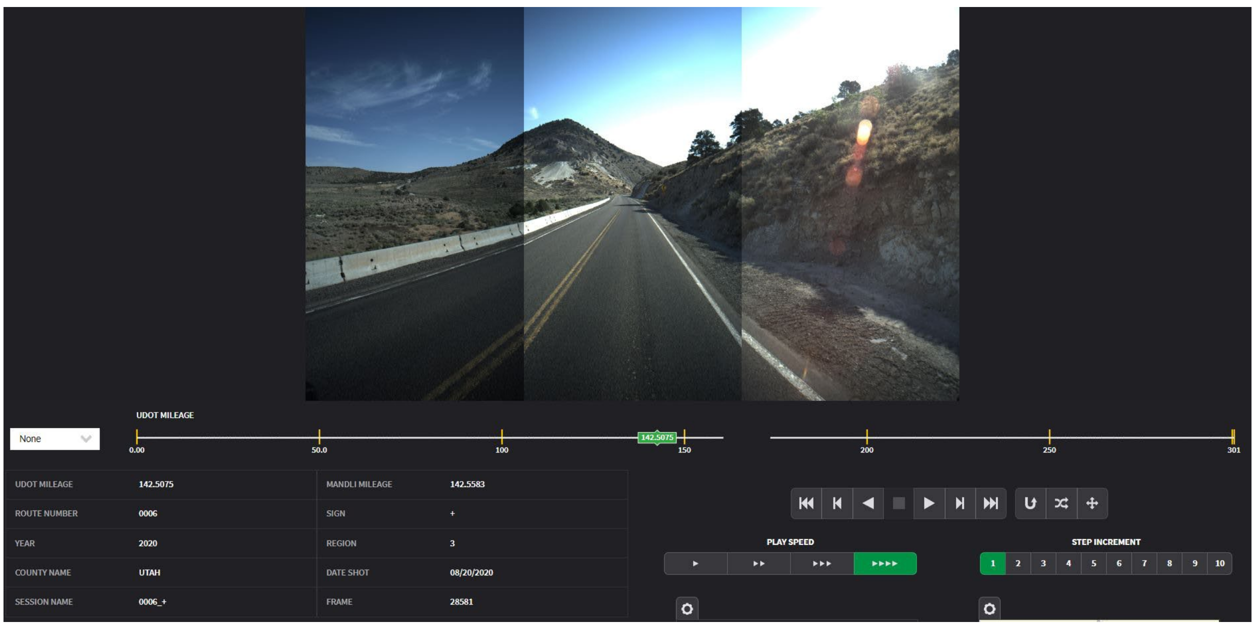

Figure 5.16 Actual Condition of the Point Listed in the Previous Figure (#4)

6. CONCLUSIONS

This project has a primary objective of aiding the Utah Department of Transportation (UDOT) in identifying hazardous locations on Utah highways and prioritizing safety improvement projects, such as removing overgrown trees and adding guardrails. The proposed method integrates machine learning algorithms and Mandli images, utilizing the FHWA rating system as the key standard for evaluating roadside safety.

The methodology employs various computer vision algorithms to automatically rank roadside safety by detecting features such as guardrails, clear zones, rigid obstacles, and roadside slopes. Notable results include a guardrail detection model achieving 93% accuracy, a logistic regression model for rigid obstacle detection achieving 100% accuracy in identifying vegetation and embankments, and a combined model for detecting rigid roadside obstacles achieving 94% accuracy. Additionally, pretrained models have been developed for clear zone detection (83% accuracy) and classifying roadside slopes into low, mid, and high categories (94% accuracy).

Utilizing the extracted features and developed algorithms, safety rankings have been assigned to road segments on five state roads: US-6, SR-10, SR-12, US-40, and SR-150. The final product is a GIS shapefile containing safety rankings and details on roadside features at each interval along these roads. This product serves as a valuable tool for traffic engineers, aiding in decision-making processes to enhance the safety levels of each road segment. With this information, UDOT can prioritize projects addressing specific locations, leading to improvements in road safety and a reduction in potential crashes.

6.1 Challenges and Limitations

The application of machine learning algorithms and computer vision technologies to assess roadside safety is a promising approach, yet several limitations and challenges must be acknowledged and addressed. First, a significant limitation is the dependency on high-quality roadside images, which may not always be readily available or accessible. Poor image quality can lead to inaccurate detection of roadside features, compromising the reliability of the results. Additionally, models developed for specific roadside features may require periodic retraining to remain effective, considering the dynamic nature of roadside conditions. The reliance on data collected in 2020 highlights the need for regular data updates, particularly regarding changing vegetation conditions. Another limitation is associated with the challenges of obtaining the necessary images. The model's development using data from only five routes, excluding interstates, may limit its representativeness for the entire state. To enhance accuracy, additional data collection and incorporation into the model are essential.

Furthermore, there is a challenge concerning potential false positives and false negatives. Computer vision algorithms may misinterpret non-hazardous roadside features as hazardous or may miss actual hazards, leading to either unnecessary or overlooked road maintenance. Human verification is imperative before decisions are made to improve identified road segments. Finally, this approach may not encompass all factors contributing to roadside safety, such as driver behavior and weather conditions. It should be considered a complementary tool to existing methods for assessing roadside safety rather than a complete replacement. Moreover, the model's design and training on rural imagery data limit its applicability to urban areas.

In conclusion, while machine learning algorithms and computer vision technologies offer significant potential for enhancing roadside safety, addressing the associated limitations and challenges is crucial to ensuring effectiveness and widespread adoption. Ongoing efforts to improve data quality, expand dataset representativeness, minimize false positives/negatives, and acknowledge the complementary nature of this approach within a broader safety assessment framework will contribute to its successful implementation.

6.2 Recommendations

To enhance the effectiveness of machine learning in roadside safety assessment, continuous data collection and model updating are crucial. Regularly updating the dataset and retraining models will ensure that the algorithms remain adaptive to changing roadside conditions, improving their accuracy over time. Additionally, expanding the dataset to include diverse road types, such as interstates and urban areas, will enhance the model's generalizability. Investments in improving image quality, human-in-the-loop verification systems, and the integration of weather and traffic data will address limitations associated with false positives and negatives, providing a more reliable safety assessment. Collaboration with transportation authorities and benchmarking against traditional methods will validate the new approach's efficacy, fostering its seamless integration into existing safety frameworks. Furthermore, future studies should explore the extension of models to urban areas, assess driver behavior's impact on safety, and incorporate public awareness campaigns to educate stakeholders about the technology's benefits and limitations. In summary, a comprehensive approach involving data refinement, model adaptation, and collaboration with relevant stakeholders will maximize the potential of machine learning in roadside safety, contributing to safer roadways and informed decision-making in transportation infrastructure planning.

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