

RESEARCH ARTICLES

# Correlating Machine Learning Classification of Traffic Camera Images with Snow-related Vehicular Crashes in New York State

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**Abstract:** Millions of motor vehicle crashes and tens of thousands of resulting deaths occur each year in the United States. While it is well known that wintry conditions make driving more difficult and dangerous, it is difficult to quantify and communicate the threat to motorists, especially in real time. This proof-of-concept research uses machine learning (ML) to approach this problem in a new way by creating a ML model that can identify snow on the road from a traffic camera image. This information is coupled with the number of coincident vehicular crashes to provide detailed consideration of the impact of snow on the road to motorists and transportation agency decision-makers. It was found that, during meteorological winter, when the ML model determined there to be snow on the road in a traffic camera image, the chance of a vehicular crash pairing with that traffic camera increased by 61%. The systems developed as part of this research have potential to assist roadway officials in assessing risk in real time and making informed decisions about snow removal and road closures. Moreover, the implementation of in-vehicle weather hazard information could promote driver safety and allow motorists to adjust their driving behavior and travel decision making as well.

**Keywords:** Image classification, Image recognition, Machine learning, Road condition, Road weather, Weather-related crashes

## 1. Introduction

Winter storms result in significant and costly disruptions to society. Globally, winter storms induce billions of dollars in economic losses and contribute to thousands of fatalities each year<sup>[1,2]</sup>. In the United States, winter storm impacts on the surface transportation sector are

most notable. Each year, transportation agencies exhaust billions of dollars in winter maintenance operations costs to provide society with an optimal level of service with respect to safety and mobility during and after winter storms<sup>[3]</sup>. These costs include winter maintenance activities such as plowing roads and applying chemical deicing treatments to limit the bond between snow and ice and the

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road pavement<sup>[4]</sup>. The Federal Highway Administration's (FHWA) Road Weather Management Program (RWMP) estimates that approximately 21% of all highway crashes in the United States each year are attributable to inclement weather conditions<sup>[5]</sup>. These 1.2 million crashes result in over 400,000 injuries and 5,300 fatalities on roads each year. Given the magnitude of these impacts, it is imperative to promote better understanding of winter storms in conjunction with increased situational awareness and decision support for the surface transportation sector.

Past studies have conducted broad assessments of winter storm climatology and impacts<sup>[6-15]</sup>. These previous analyses often considered differences among regional winter storms ranging from the Western United States and High Plains to the Mid-Atlantic and East Coast. Western and High Plains winter storms often have unique synoptic evolutions given contributions from mesoscale and microscale terrain influences<sup>[7,8,10,11]</sup>. Moreover, these storms tend to impact less populated, more rural regions in the Intermountain West. East Coast and Mid-Atlantic winter storms, by contrast, impact the dense urban population centers along the Interstate 95 Corridor and often have ample access to moisture resulting in larger impacts<sup>[6,9,12-15]</sup>. Several studies have attempted to categorize the impacts of winter storms through metrics known collectively as winter severity indices<sup>[16-23]</sup>. These techniques leverage different mathematical, statistical, and machine learning (ML) techniques to associate meteorological inputs (e.g., temperature, wind speed, duration, ice accumulation) with subsequent storm impacts (e.g., vehicular crash rates, winter maintenance costs, societal disruption). Many of these metrics place emphasis on understanding surface transportation impacts associated with winter storms<sup>[24-26]</sup>.

An additional body of literature has focused on weather-related vehicular crash analyses<sup>[27-31]</sup>. Many of these studies have taken a relative risk-based approach to characterize the expected increase in both individual exposure and likelihood of being involved in a weather-related crash during various conditions such as snowfall. In all instances, snowfall is associated with a statistically significant increase in both exposure and likelihood for vehicular crashes. Such findings align with the aforementioned deleterious impacts of winter storms on surface transportation.

The discussion of winter severity indices and weather-related vehicular crash analyses leads to the unique application of ML and image processing techniques to better understand how winter storm conditions are changing directly on roadways in real-time. Khan and Ahmed<sup>[32]</sup> and their subsequent work<sup>[33]</sup> present some of the first work with a direct application of ML techniques to detect

snow from in-vehicle forward facing camera imagery in Wyoming. Their work builds on earlier assessments that used traditional image processing, feature extraction, and classification techniques to identify weather conditions from camera imagery without the use of ML techniques<sup>[34-36]</sup>. Additionally, they integrated ML-based image classification techniques<sup>[37]</sup> to automate the process.

With the broader accessibility of ML tools<sup>[38]</sup>, this proof-of-concept research study aspires to integrate ML image recognition of snowy conditions with an understanding of vehicular crash occurrence on roadways in New York State during the 2020-2021 winter season. The significance and importance of this work is to provide additional understanding and resources for real-time mitigation and decision support with respect to winter storm surface transportation impacts. This insight can be beneficial to both transportation agencies as well as the traveling public to promote knowledge of when and where road conditions are deteriorating the most.

## 2. Methods and Data

### 2.1 Scope

Geographically, this research was constrained to New York State and serves as a proof-of-concept study. New York State is an ideal region of study because it receives considerable snow in the winter and has significant motor vehicle traffic due to its large population. Also, traffic camera images and motor vehicle crash reports were available for New York State. The data for the study were collected during the meteorological winter of 2020-2021, which ran from 1 December 2020 through 28 February 2021. Meteorological winter was chosen as the study period because it is when most of the impactful snowfall occurs in New York State<sup>[12,17]</sup> and therefore when the risk of snow-covered roads is most relevant.

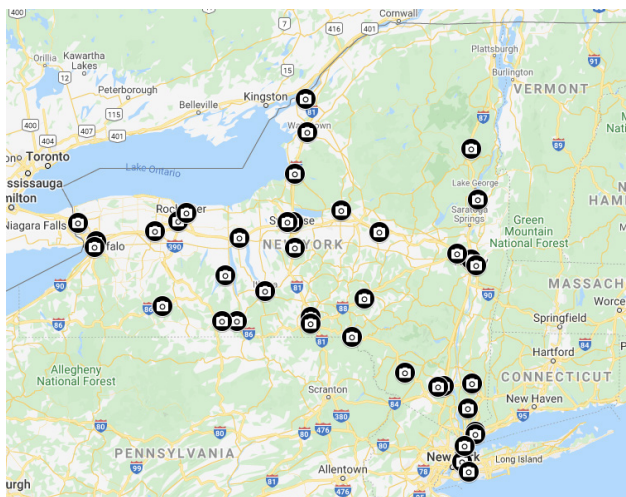
### 2.2 Data Collection

To obtain both the traffic camera images and motor vehicle crash reports, a web-scraping technique was employed. The images and reports were sourced from 511 New York, a free service administered by the New York State Department of Transportation (NYSDOT) offering information on transportation services and conditions throughout New York State<sup>[39]</sup>. The 511 New York website displays thousands of real-time crash reports and traffic camera images from throughout the state, but no archive was available. Therefore, two web-scraping servers were created, one to collect and store traffic camera images and

the other to collect and store crash reports.

The traffic camera server ran every 30 minutes, each time retrieving the latest image from the 511 New York website for each of 40 traffic cameras (Figure 1). Over the course of meteorological winter, approximately 250,000 traffic camera images were collected (Figures 2-3). The collection interval was limited to 30 minutes and the number of traffic cameras used was limited to 40 due to computational constraints of the server and to make this preliminary analysis simpler. These 40 cameras were designated prior to the start of the study period and were chosen based on their location and the quality of their images. Extensive coverage of the study area was desired, especially along densely populated road corridors with more vehicular traffic, and to decrease the average distance between crash reports and traffic camera images. A lower average distance was desired because road conditions nearby are more likely to be similar than road conditions many kilometers apart, especially considering the highly variable nature of snowfall in the study area (e.g., lake-effect). Also, traffic cameras with large, unobscured views of the roadway were preferred to mitigate the noise produced by non-roadway surfaces such as trees or overpasses. Traffic cameras on interstate and primary highways as well as secondary and local streets were used to ensure the model would be applicable in both settings.

A similar server was also set up to collect crash reports. All crash reports on the 511 New York website within the bounds of New York State were collected and stored. The server ran every ten minutes to check for new reports. Each report contained the latitude, longitude, and time of the crash. Over the course of the study period, roughly 6,000 crash reports were collected (Figure 4).



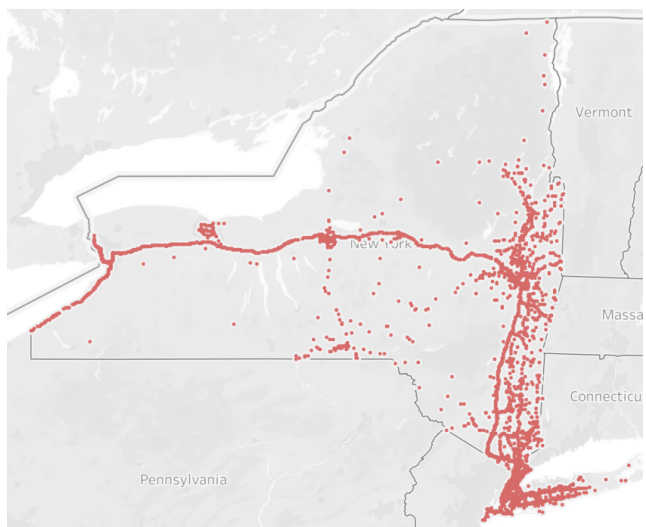
**Figure 1.** Locations of 40 traffic cameras whose images were acquired from 511 New York.



**Figure 2.** Example traffic camera image of a snow-covered roadway.



**Figure 3.** Example traffic camera image of a clear, dry roadway.



**Figure 4.** Locations of 6,000 traffic crashes collected over the study period from 511 New York.

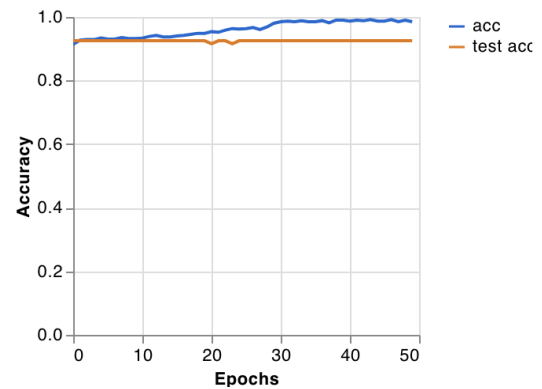
### 2.3 Image Classification

The research used a ML approach to determine whether there was snow on the road in the traffic camera images. To build the ML model, an open-source program called Teachable Machine from Google was used [38]. Teachable Machine is a web-based graphical interface for building simple image classification models. Teachable Machine uses a technique called transfer learning to train models efficiently. Transfer learning involves building from a pre-trained neural network by using the output of the pre-trained model as the model input. Specifically, Teachable Machine image models learn from a pre-trained MobileNet image classification model that is trained on many common objects.

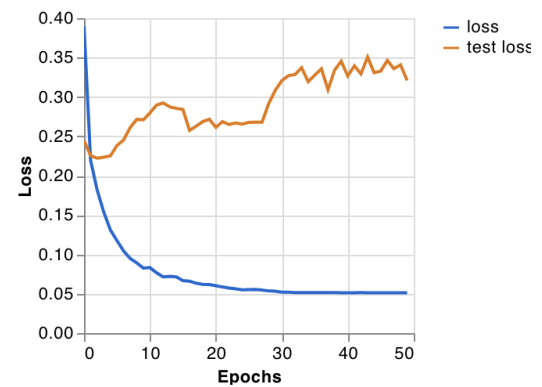
To create the training data for the model, 1000 random traffic camera images from around the state were manually sorted into one of three categories: “snow”, “no snow” or “unclear”. If any amount of snow was visible on the roadway in a traffic camera image, that image was placed in the “snow” category. This did not include old snow piles on the side of the road or snow anywhere off the road. If there was no snow visible on the roadway, the traffic camera image was sorted into the “no snow” category. If no confident determination could be made as to the presence of snow on the roadway, the image was placed in the “unclear” category. This happened primarily at night when the lack of light meant that the road was often not visible. It also happened during the day if the traffic camera was obscured, offline, or had moved so that it was no longer facing the roadway. The images in the “unclear” category were not used to train the model.

Once the images were sorted, the images from the “snow” and “no snow” categories were uploaded to Teachable Machine and used to train an image classification model using the default Teachable Machine training settings. The default training settings were 50 epochs, a batch size of 16 images and a learning rate of 0.00005. The model was moderately successful (75%) when it did identify snow, but it failed to correctly classify 62% of snow images based on the training data. This is likely because images without snow (659) greatly outweighed images with snow (52) in the training data. Once the model was trained, a test on 321 verification images that were not used in training, also manually sorted into the same categories, found that its probabilistic output had a mean square error of 6.05% (Table 1). Deterministically, the model was 92.4% accurate when tested on the same set of verification images (Figure 5).

Accuracy per epoch



Loss per epoch



**Figure 5.** Accuracy per epoch (up) and loss per epoch (bottom). The blue line is during training while the orange line is during testing.

**Table 1.** Confusion matrix for test data output.

True Class	Predicted Class	
	Snow	No Snow
Snow	9 (75%)	15
No Snow	3	294 (95%)
Total	12	309

Once the model was trained and its accuracy verified, it was used to automatically sort the remaining 247,914 traffic camera images that were accumulated during the winter, placing them into either the “snow” or “no snow” category.

### 2.4 Image-Crash Pairing

To determine the risk analysis capabilities of the image

classification model, as well as to estimate the risk to motorists of snow-covered roads, an image-crash pairing approach was used (Figure 6). For each of the crash reports collected over the winter, the best traffic camera image in our archive was found, creating an image-crash pairing. This was accomplished using a simple index: the absolute value of the minutes between the traffic camera image being taken and the crash occurring plus twice the distance between the traffic camera and the crash site in kilometers. The image with the lowest index was chosen as the pairing for each crash, unless the lowest index was more than 80, in which case the pairing was rejected and not included in the analysis. An index system was used because conditions are more likely to be similar between a traffic camera image and a corresponding crash if they are closer in both time and space, thereby making the risk analysis more valid. Pairings with high indexes were rejected because they were far enough apart in time, space, or both that the conditions were unlikely to be similar between the crash and the image. This process resulted in an average distance of 11.7 km and an average temporal difference of 7.4 minutes across the database of image-crash pairings.

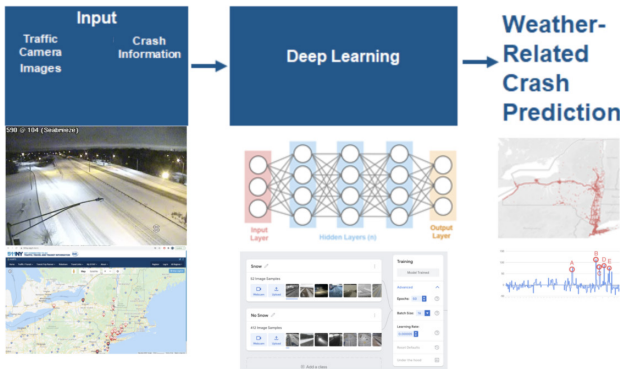


Figure 6. Flowchart summary of logic for image-crash pairing.

### 3. Results and Discussion

It was found that large scale snowstorms had an impact on crashes in New York State. Nearly all major snow events in the study region caused a significant positive anomaly in crashes across the state, and nearly all significant positive anomalies in crashes were caused by snowstorms. Figure 7 and Table 2 show this correlation clearly. Although there was a clear relationship between winter storms and crashes, there was not a clear relationship between the severity of the winter storm and the degree of the anomaly. This is potentially due to the presence of many other factors, including the timing of the storm.

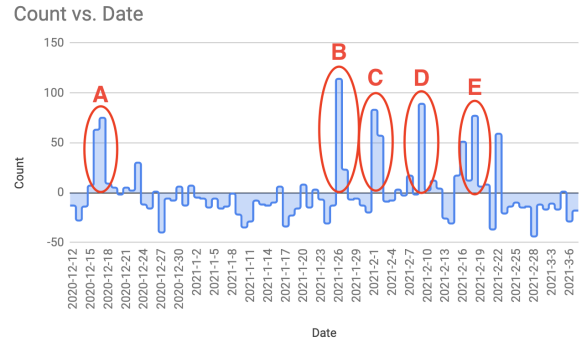


Figure 7. Daily crash counts for the study period with large positive anomalies circled and labeled according to larger winter storms identified in Table 2.

Table 2. Event descriptions for winter storms during the study period associated with large positive anomalies in crash counts identified in Figure 7.

Event	Date(s)	Description
A	16 - 17 Dec 2020	Major nor'easter impacts the Northeast, dropping more than 3 feet of snow in parts of New York State
B	26 Jan 2021	Minor winter storm impacts New York State, including New York City
C	1-2 Feb 2021	Major nor'easter impacts the Northeast, dropping feet of snow in parts of New York State, especially in southern and western portions of the state
D	9 Feb 2021	Minor winter storm impacts Upstate New York
E	18 Feb 2021	Major winter storm impacts southeast New York State

#### 3.1 Crash-Image Correlation

The relationship between snow on the roads as detected by the traffic camera model and the occurrence of motor vehicle crashes was strong. Of the 247,914 classified traffic camera images included in the analysis, 13,744 had snow as detected by the ML traffic camera model (5.54%). Of the 5,792 traffic camera images with a crash pairing, 500 had snow (8.63%). This means that, of the images with no snow, 2.26% had crashes, whereas of the images with snow, 3.64% had crashes. This represents a 61.0% increase in the chance of a crash if you are somewhat nearby (on average 11.7 km and 7.4 minutes) from a traffic camera image that the model indicates has snow as opposed to a traffic camera image that the model indicates as without snow.

#### 3.2 Limitations

There were some limitations to this preliminary proof-

of-concept study. One limitation was in the accuracy of the ML model. While sorting the images manually, it was at times difficult to determine the state of the road especially at night, meaning that more nighttime images were discarded and played a smaller role in training the model. This lack of training data likely caused the model to be less accurate at detecting snow at night. Also, the model struggled in cases where the road took up a small percentage of the traffic camera image frame. In general, the model suffered from a lack of advanced structure and tuning due to the use of Teachable Machine, which made it more straightforward to build the model. The model was effective at knowing when there was not snow. Most of the non-snow images were classified correctly, but it missed many snow images which would have made it less useful in an operational scenario. It is possible that the correlation between snow and crashes would have been stronger if more of the snow images had been classified correctly.

Another limitation was in the physical distance and time gap between the crashes and the corresponding traffic camera images. The data collection server tracked a limited number of traffic cameras due to computational constraints, and a limited number of traffic cameras exist in certain parts of New York State. The server also collected images every 30 minutes, meaning crashes and images could be up to 15 minutes apart. Considering the tight gradients in snowfall on a local level, the road conditions at the location of a traffic camera image and its corresponding crash could be quite different, thus weakening the correlation.

A final implication was the lack of a control regarding the traffic volume. It is probable that the presence of snow on roads reduced traffic volumes, and therefore it is impossible to determine from these results alone the true risks of snow on roads to motorists who do choose to drive. It is likely that had this research controlled for traffic volume, the correlation between snow on roads and crashes, and thus the relative risk and exposure, would have been even higher, considering many people choose not to drive when there is snow on roads.

#### 4. Summary and Conclusions

This study presents a proof-of-concept application of Google's Teachable Machine model to automate identification of snowfall in New York State traffic camera images during the 2021-2022 winter season. Moreover, this analysis integrated the classified image output in conjunction with vehicular crashes sourced from a New York State transportation agency website. It was found that the presence of snowfall on traffic camera imagery was as-

sociated with a 61% increase in the likelihood of a crash. Additionally, the image classification model was found to be 92.4% accurate relative to an initial training data set.

The implications of this work demonstrate the applicability and feasibility of combining previous ML image classification work<sup>[32,33]</sup> with weather-related vehicular crash analyses<sup>[28-31]</sup>. Moreover, this work demonstrates how social media and crowd-sourced traveler information can be used to provide additional real-time insights and analytics for both transportation agencies and end users. Such analytics may not only promote increased safety and mobility during winter storms, but also serve as an enabler to future technologies such as connected and autonomous vehicles operating during inclement weather conditions.

Immediate next steps are to expand the existing data set and analysis to include additional winter seasons and more traffic camera images throughout the state for a more robust sample size. It may also be worthwhile to include information from adjacent states throughout the region as well to augment the existing data sample. Future extensions of this work include applications to other weather conditions such as rain and low visibility scenarios. Additionally, these methodologies should be applied to other regions as well to determine if the modeling framework and algorithms are devoid of any regional bias in their usability. Last, stakeholder engagement with transportation agencies and the weather enterprise to showcase these methodologies will promote more widespread adoption and further development of additional techniques to safeguard surface transportation during winter storms.

#### Author Contributions

Lead author Chang was responsible for the raw data acquisition and database development, machine learning analysis, and preliminary draft of the manuscript. Coauthor Walker was responsible for the overall project idea, project supervision and management, mentoring of Lead author Chang, and contributed to writing and revision of the manuscript.

#### Conflicts of Interest

The authors declare no conflict of interest.

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