Automated Real-Time Weather Detection System using Artificial Intelligence

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1. Problem Statement

Adverse weather conditions, such as snow, rain, and fog, can directly impact roadway safety, by reducing the visibility and roadway surface friction, negatively affecting vehicle as well as drivers' performance, and potentially increasing required stopping sight distance. The Federal Highway Administration (FHWA) reported that adverse weather is responsible for around 21% of total vehicle crashes, 19% of crash injuries, and 16% of crash fatalities each year in the U.S. (*1*). Previous studies concluded that weather-related factors could increase traffic fatalities and injuries by 25% and 45%, respectively (*2*, *3*). Several studies have concluded that adverse weather can increase the severity of crashes and involve multiple vehicles (*4*). Falling and blowing snow, blizzards, fog, and rain weather can result in a sudden reduction in visibility on the roadways. Moreover, the road surface friction could be also reduced significantly due to icing and hydroplaning. The low surface friction of snow-covered roadways coupled with reduced visibility from fog, and frozen rain/ falling snow could result in dangerous conditions for drivers, making it one of the major causes of motor vehicle crashes. According to the FHWA, approximately 688 fatal crashes, 41,860 injury crashes, and 186,076 property damage only (PDO) crashes occur every year in the U.S. because of snow (*1*). In addition, many pile-up crashes have occurred in recent years due to the presence of fog which caused many fatalities, injuries, and property damages. For instance, a multi-vehicle crash due to dense fog occurred on I-94, Michigan on January 9, 2015, which caused the death of one person, injuries of approximately 23 people, and the closure of the interstate for longer than one day (*5*). The study of Moore and Copper noted that despite a 20% decrease in traffic in thick fog, there was an increase of 16% in the total number of personal injury accidents (*6*). Another study revealed that crashes occurred in heavy fog tend to involve multiple vehicles (*7*). Considering rainy weather, it was found that the risk of injury crashes in rainy weather conditions could be two times greater than in clear weather conditions (*8*). Several studies concluded that crashes increase due to vision obstruction during heavy rainfall by 100% or more (*8*), while others found more moderate but still statistically significant increases (*9*). However, in the state of Wyoming, the number of snow-related crashes are particularly significant. Merely in winter 2018, there were 1,438 snow-related crashes, which resulted in fatalities, extended closures, and significant economic loss (*10*). This is mainly due to Wyoming's adverse winter weather events (such as low visibility and icy road surface from blizzard conditions) and the state's roadway and traffic flow conditions (i.e., a large number of low traffic volume rural two-lane highways, and mountainous freeways that have high percentage of heavy inter- and intra-state freight traffic). In practice, the negative impact of snowy weather on roadway safety can be effectively mitigated through the implementation of various safety countermeasures, such as Dynamic Massage Sign (DMS) and Variable Speed Limit (VSL) (*11*, *12*). Nevertheless, these countermeasures require accurate and real-time road surface and weather information to operate effectively and reliably. Therefore, the detection of real-time weather condition and providing drivers with appropriate warnings are crucial for safe driving during adverse weather conditions, including snow, in Wyoming. This is considered by the Wyoming Department of Transportation (WYDOT) Travel Information Service as a primary task (*13*).

The state-of-practice of collecting and broadcasting road weather information to travelers has been primarily based on roadside weather stations and Road Weather Information Systems (RWIS). Although RWIS can provide quantitative weather data, such as temperature, humidity, wind speed, visibility, and precipitation, these systems are expensive. According to the U.S. Department of Transportation, the average total cost of implementing a RWIS is about $52,000 per unit (*14*). Therefore, their widespread implementation might not be feasible. In addition, sensors on the weather stations are usually not mounted at the road surface level. Many weather conditions, such as blowing snow, may reduce the visibility only at the road surface level due to the accumulation of snow on the side of the road and wind, especially in mountainous regions. In such cases, the visibility distance at higher elevations identified by weather stations might not represent the actual visibility and road surface conditions. Moreover, these weather stations are location-specific and cannot provide real-time trajectory-level weather data. In comparison, the use of fixed webcams, as well as in-vehicle cameras, tends to be a more cost-effective and reliable alternative, and could be installed where power and communication are available. Also, they can provide road weather conditions including the surface unlike RWIS.

Figure 1 shows the existing Webcam locations in Wyoming Road Network. Merely on the 402-mile Interstate Freeway 80 (I-80) in Wyoming, currently there are 56 fixed webcams with each location having three views of the roadway, including west bound, east bound, and road surface. The real-time road surface conditions can also be collected unlike RWIS since the webcams are also capable of providing images of the road surface, as shown in Figure 2.

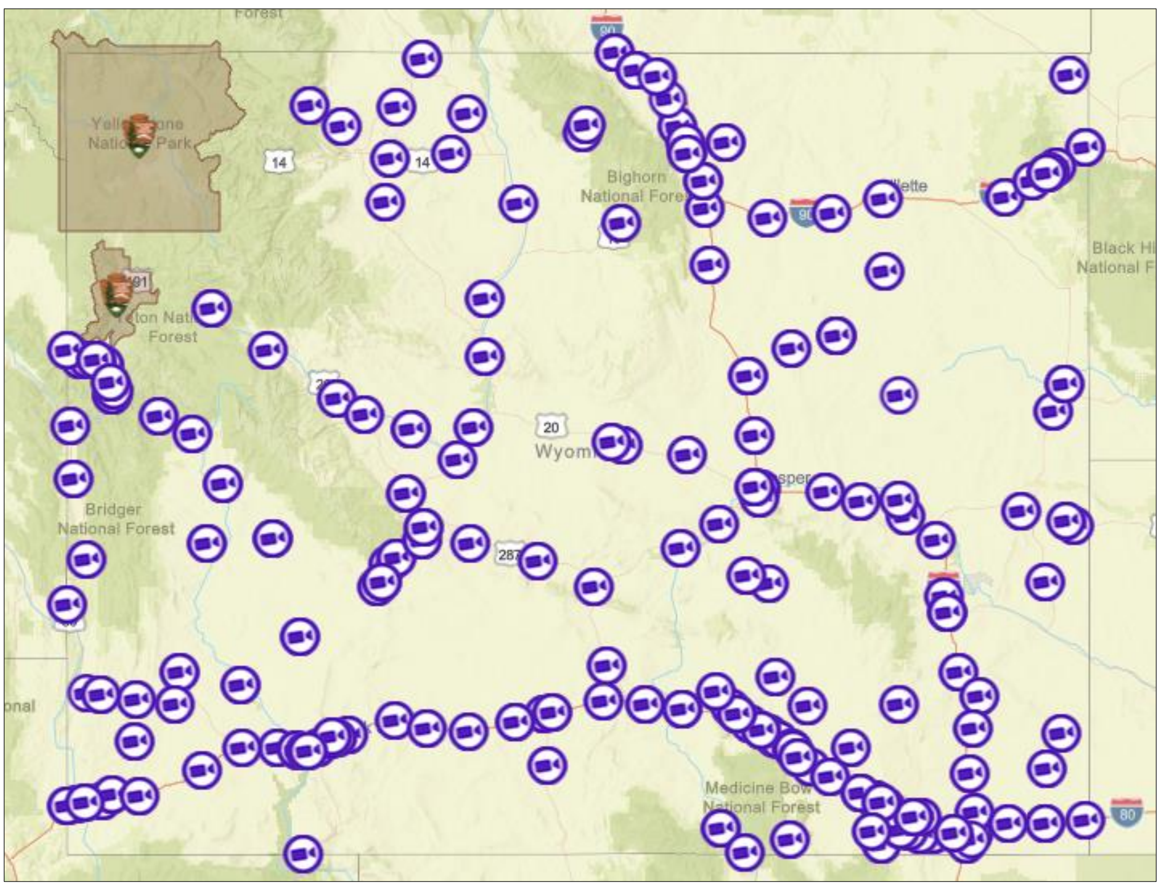
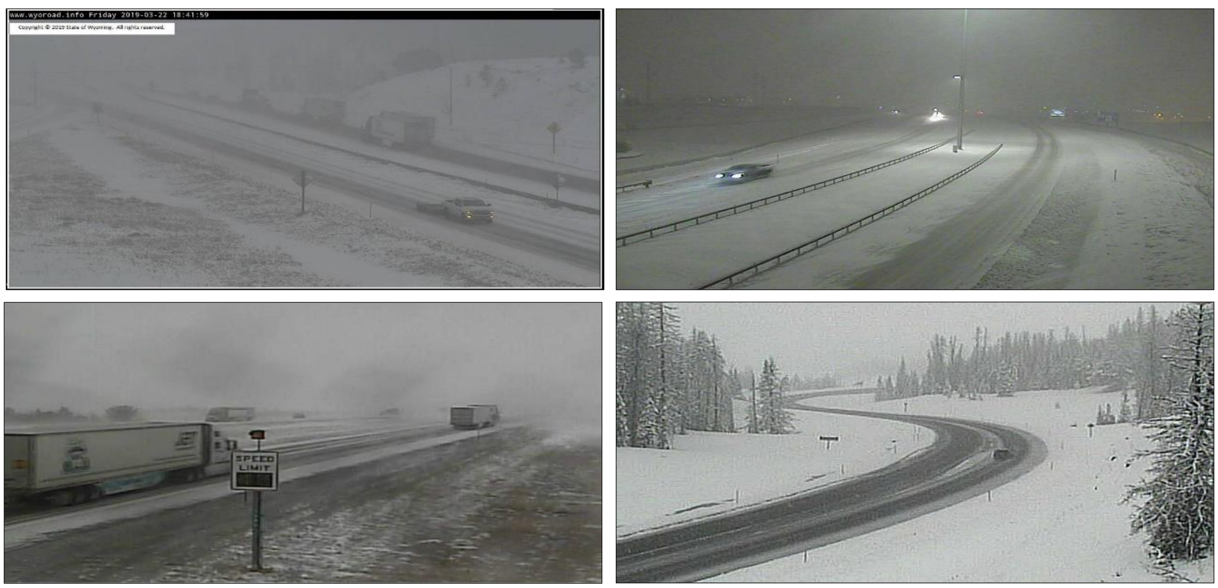


Figure 1 Webcam locations in Wyoming Road Network **(Source: wyoroad.info)**

a) Clear Weather (EB, WB, and Road Surface Images collected from WYDOT webcams)



b) Adverse Weather (EB, WB, and Road Surface Images collected from WYDOT webcams)

Figure 2 *Sample Images in Adverse and Clear Weather Collected from Webcams in Wyoming (Source: wyoroad.info)*

Nevertheless, there are a couple of limitations with existing webcam and in-vehicle video cameras for real-time weather detection. One of the major limitations is the amount of data collected and the manual resources needed to reduce and process the images collected. In addition, under extreme adverse weather conditions, particularly, when snowstorm or blizzard events occur, the low visibility might impede webcams recognizing road surface level weather. Although in-vehicle cameras can well address this issue, regular vehicles might have to cancel their trips under such weather events, which makes using a regular vehicle for weather data collection not always applicable. As mentioned by the WYDOT snowplow priority plan, the WYDOT snowplow crews will provide service on interstates, high volume highways, principal arterial and urban routes up to 24 hours a day with a goal of maintaining clear roadways for driving safely at reasonable speeds (*10*) . In current practice, reporting of real-time road surface winter weather information is mostly based on snowplow drivers. In Wyoming, the WYDOT defined 8 and 9 codes (code #1 to code #7) to represent various road surface weather conditions. Snowplow truck drivers will manually select a code to describe the prevailing surface weather condition of a road segment based on his/her experience, and report the code to WYDOT Traffic Management Center (TMC). However, due to variation of how various weather conditions might be perceived by individual drivers, there might be inconsistencies between reported road weather conditions to TMC. In addition, existing weather codes cannot differentiate the intensity of adverse weather conditions, indicating that the code reported to TMC might not accurately capture the actual adverse weather condition.

The rapid evolution of Information Technologies (IT) presents opportunities of using Machine Vision and Artificial Intelligence to provide image-based automatic detection and analysis of real-time road weather conditions. Machine Vision is an integration of a series of technologies, software and hardware products; it is the science of getting computers to automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty. The overall Machine Vision process includes planning the details of the requirements and project, and then creating a solution. During run-time, the process starts with imaging, followed by automated analysis of the image and extraction of the required information. Given the advantages of Machine Vision technology, such as real-time processing of road surface level weather conditions, accuracy of weather detection, cost-effectiveness, etc., it has been extensively used in various fields of engineering for image classification, pattern recognition, and text categorization (*15*).

With consideration of the limitations of the existing WYDOT weather detection systems, and in view of the opportunity of the emerging automatic video-image processing technologies, this research aims at developing an affordable weather detection system, which will use video images collected primarily by the WYDOT roadside fixed webcams and secondarily by examining the feasibility of extending the algorithms to snow plows trajectory-level cameras. It is worth mentioning that WYDOT operates and maintains many roadside webcams. It is not feasible for WYDOT TMC operators to review and process them timely. The weather information will be processed based on Machine Vision techniques. Eventually, the product of this research will assist WYDOT staff with providing road users with accurate and reliable road surface weather condition, which will result in safer travel decisions and more conservative driving behaviors to mitigate the negative impacts of adverse weather on traffic safety.

2. Preliminary Literature Review

2.1 Weather Detection Systems

In the U.S, several weather detection systems have been adopted by state DOTs to warn drivers about sudden drops in visibility. In 1993, a fog detection and warning system were implemented along Interstate 75 near Calhoun, Tennessee, which includes a three-mile fog detection area spanning north and south of the Hiwassee River and an eight-mile warning zone on each approach to the fog-prone area (*16*). In 2006, a project was initiated to upgrade the original system to current technology. Driver safety issues due to visibility problems have improved significantly since the system has been in place, with only one fog-related accident being recorded in 2001. The fog warning system consists of six static warning signs with flashing beacons, ten Changeable Speed Limit Signs (CSLS), ten overhead DMS, and two Highway Advisory Radio (HAR) transmitters.

In 1999, Alabama DOT implemented a low visibility warning system stretched over a 6.2 miles long corridor on I-10 near Mobile (*16*). This system consists of 6 forward scatter Scientific Technology brand fog detectors, 11 pan/tilt/zoom closed-circuit cameras, 14 fixed closed-circuit cameras, 3 dot matrix VMSs, 1 portable VMS, streetlights, and fiber optic connections. The fog-mitigation system was developed because of a severe 193-car accident in May of 1995 on I-10. Speed limits and Dynamic Massage Signs (DMS) are displayed based on the current visibility conditions. However, the main problem with Alabama's system is that the fog sensors are not capable of distinguishing between finer gradations of fog as are made for airports visibility detection. In 2008, a system upgrade was performed to the fog system. These upgrades included updating devices, improving the method of communication with these devices by going from a point-to-point system to Ethernet, and the addition of Radar Vehicle Detection (RVD) devices.

Due to the high traffic volume and frequent formation of dense fog, Utah DOT implemented a low visibility warning system on I-215 (*17*). The system consists of four visibility sensors, six visibility detection sites and two DMSs. Visibility distance measured in real-time and loop detector measures the speed, length, and lane of each vehicle. An evaluation of the warning system indicated that overly cautious drivers speed up when advisory information was displayed, resulting in a 15 percent increase in average speed from 54 to 62 mph. This increase caused a 22 percent decrease in speed variance from 9.5 to 7.4 mph. Reducing speed variance enhanced mobility and safety by promoting more uniform traffic flow and minimizing the risk of initial, secondary, and multi-vehicle crashes.

The California Department of Transportation (Caltrans) deployed a fog detection and warning system on Highway 99 near Fresno in 2007 (*18*). The entire central valley region is susceptible to Tule fog, which can reduce visibility tremendously, sometimes near to zero. This area has experienced numerous multiple vehicles crashes because of the fog, most recently in 2007, when a 108-car pile-up caused two deaths and nearly 40 injuries, and closed the highway for more than twelve hours. The Fog Detection and Warning System (FDWS) system consists of visibility sensors, speed detectors and cameras to detect congestion and visibility problems that could affect driver and passenger safety.

In summary, the aforementioned low-visibility warning systems revealed that, in spite of having many positive outcomes such as reduction in speed variability and achieving more harmonious traffic flow, and significant reduction of visibility-related crashes, these systems have several limitations. Primarily, these systems are mostly based on weather stations which do not necessarily represent real-time weather conditions of the roadway. Moreover, these systems are not cost effective and require lots of technological support, and maintenance.

2.2 Weather Detection Algorithms using Machine Vision

In comparison with the existing weather station-based systems, image-based weather detection technique using Machine Vision tends to be more effective for real-time roadway weather determination. Existing image-based snow detection methods mainly focus on the segmentation and the removal of snow pixels from video images. In later 1990s, Pomerleau (*19*) developed a weather detection system by estimating the reduction of contrast between consistent road features, such as lane markings, shoulder boundaries, and tracks left by other vehicles, at various distances in front of the vehicle. The effectiveness of the weather detection system was tested using simulated fog images, as well as real-time images, from in-vehicle cameras, which concluded that the system could identify all possible situations of low visibility caused by adverse weather conditions. Hase et al. (*20*) proposed a method which removes snowfall noise from successive images recorded by a TV camera. They used a temporal median filter considering that most of the time the pixels are unaffected by snow. Garg et al. (*21*) concluded that simple temporal filtering methods are not effective in removing snow since they are spatially invariant and hence degrade the quality of the image in regions without snow. Therefore, they developed a method which can explicitly detect pixels affected by snow and remove the contribution of snow only from those pixels. However, their model assumes that all snowflakes have the same size and fall at almost the same velocity relative to the camera and hence their algorithm might fail to distinguish rain from other moving objects. To overcome this problem, Zhang et al. (*22*) proposed a method using k-means clustering and chromatic constraints to reduce false detections. However, their method cannot be used online because the k-means clustering algorithm can only be applied to the entire video sequence. Another model, proposed by Brewer et al. (*23*), detects snow streaks by detecting their intensity spikes. They reduce false detections based on the aspect ratio and the orientation of the streaks. Khan et al. (*24*) extracted Local Binary Pattern (LBP) based features from snowy images and used three different classification algorithms to detect snow from an in-vehicle video camera. To train the snow detection models, two texture-based image features including gray level co-occurrence matrix (GLCM) and local binary pattern (LBP), and three classification algorithms: support vector machine (SVM), k-nearest neighbor (K-NN), and random forest (RF) were used. Results show that the highest overall prediction accuracy of the models based on the GLCM features was found to be around 86%, and the models considering the LBP based features provided a much higher prediction accuracy of 96%.

In addition to snowy weather detection, different approaches to image-based weather detection can be found in the literature. For instance, Hautiére et al. (*25*) used a disparity map for visibility determination and tested the system in sunny, foggy, and dense foggy weather, which provided stable visibility estimation in all weather conditions. Boussard et al. (*26*) updated the method by adding the impact of vehicle dynamics in the algorithm and found similar results. Roser et al. (*27*) classified adverse weather into three categories (clear, light rain, and heavy rain) based on support vector machine (SVM) classifier and five image features: local contrast, minimum brightness, sharpness, hue, and saturation. They concluded that light rain condition is the most difficult to recognize compared with the other two categories. Yan et al. (*28*) utilized a dataset of 2,500 images, extracted from the video captured by an in-vehicle video camera, to detect sunny, cloudy, and rainy weather conditions. They selected hue, saturation, brightness, and gradient amplitude of the images as classification parameters and used Real AdaBoost, a powerful algorithm often used in pattern recognition, to train the weather model. Zhang et al. (*29*) proposed a fog detection technique using Support Vector Machine (SVM) and nine different images features and found a maximum detection accuracy of 78.5%. Another study utilized Grey Level Co-occurrence Matrix (GLCM) based image features and SVM classifier to detect fog and tested the system using both synthetic and real images of the foggy condition and found around 97% and 85% accuracy, respectively (*30*).

Previous Weather Detection Studies by the Research Team

The research team has previously done extensive research related to weather detection for fog, snow, and rain, using various innovative techniques including vision-based machine learning. One of the earliest works by the research team related to weather detection system was conducted in the state of Florida, where a portable visibility warning system was developed for the safety of highways using inexpensive and commercially available components (*31*). The system can continuously detect any reduction in visibility below a certain limit that would be considered hazardous for normal traffic flow conditions and can report this information to the appropriate TMC. The visibility detection system consisted of several components, as can be seen in Figure 3.

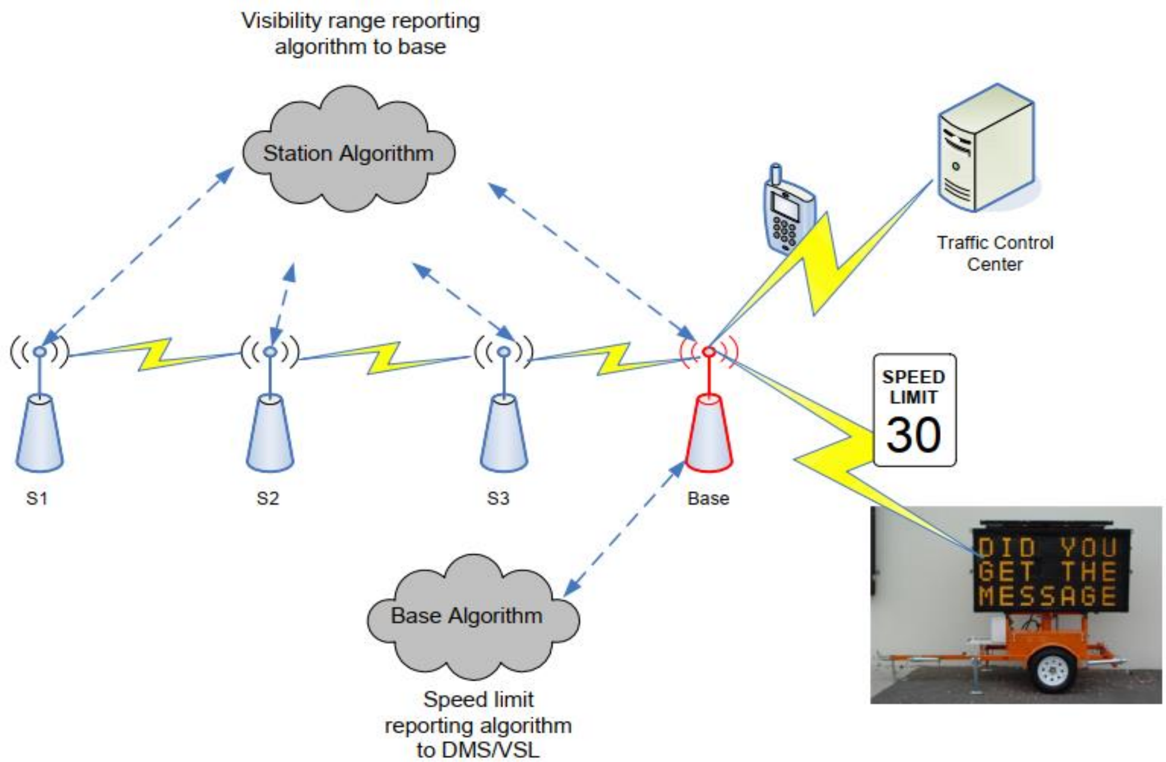


Figure 3: Florida Mobile Fog Detection System Components (31)

The hardware was composed of four stations, each connected to a visibility sensor and each of these four stations was monitored and controlled by a microcontroller installed in a unit attached to it. One of the stations performed as a base station which carried out all the communication processes between different stations, TMC, and DMS. Each of the stations contained several components, including radio antenna, GPS, visibility sensor, XBee radio, minicomputer, USB hub, power regulator, power distributor, and a battery. The components of the base and the station are shown in Figures 4 and 5, respectively. The visibility system was autonomous in its operation and decision-making. It continuously monitored visibility, and whenever hazardous conditions were detected, it automatically generated warning messages that can be displayed to motorists. Two types of messages (speed advisories and warning messages of poor visibility) were automatically generated using a computer algorithm based on the measured visibility distance and the maximum safe speed.

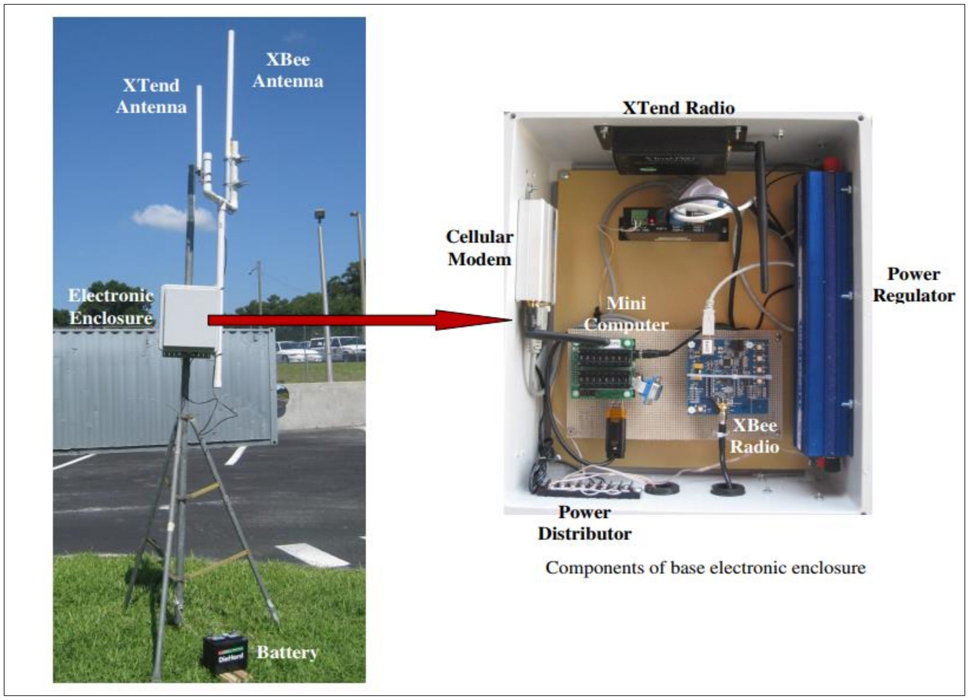


Figure 4: Base Components (31)

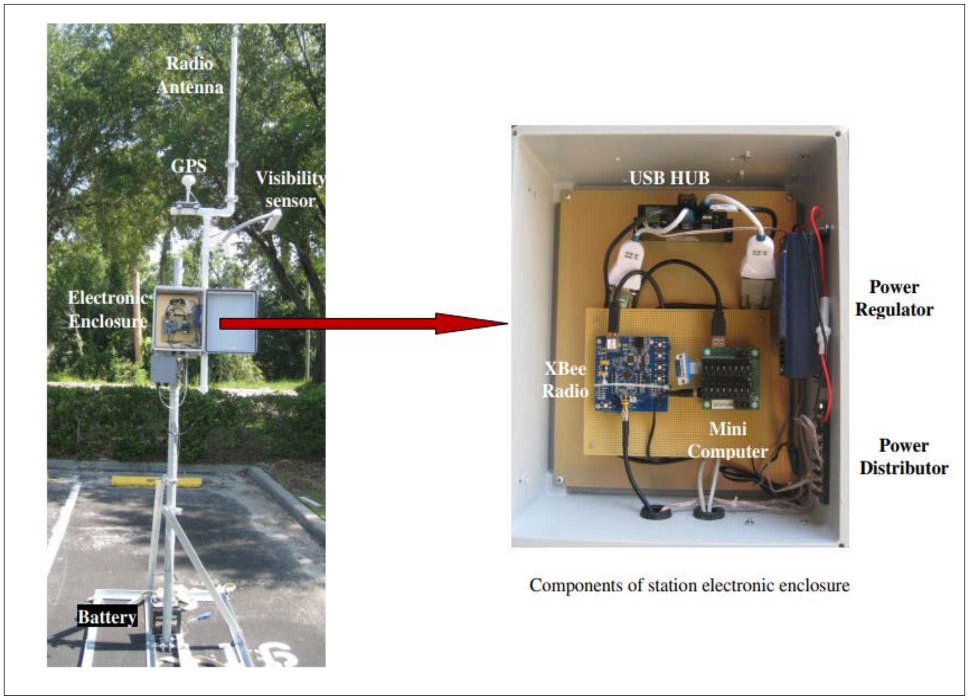


Figure 5: Station Components (31)

The research team also utilized the Second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) data for weather identification. Note that SHRP2 NDS is the largest study undertaken on naturalistic driving behavior in the US (*32*). To effectively extract data of trips occurring in adverse weather condition from the massive SHRP2 NDS dataset, two unique methods were developed by the research team (*33*, *34*). The first method used weather data from the National Climate Data Center (NCDC). The NCDC archives weather data from various weather stations nationwide, including radar, satellites, airport weather stations, and military weather stations. Among these data sources, the airport weather stations proved to be the most beneficial to identifying adverse weather events. To identify the potential location of trips occurring in adverse weather condition, a buffer zone of 5 nautical miles (n.m.) around each weather station was defined as a zone of influence. NDS trips were then requested based on the daily weather information to identify all trips impacted by adverse weather as shown in Figure 6.

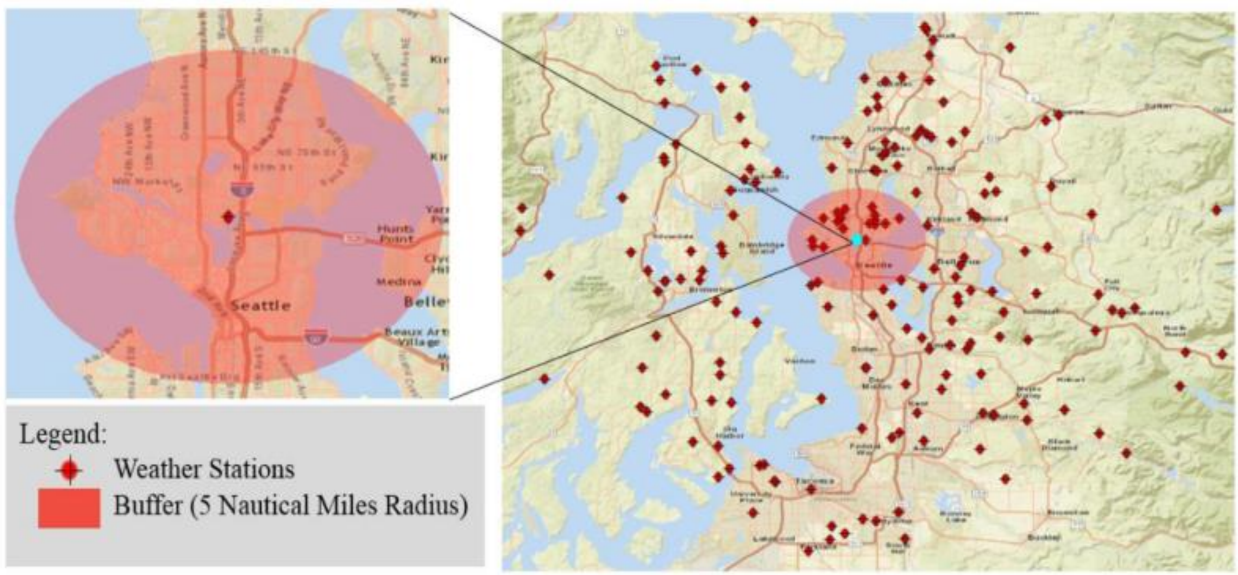


Figure 6: Weather Stations and their 5 n.m. Coverage Area (*33*)

The second method utilized weather-related crashes to identify potential locations of trips occurring in foggy weather. This method considered each weather-related crash location as a center of the influence zone and similar to the previous method, a buffer zone of 5 n.m. was used to identify trips occurred in adverse weather. Once the video data were acquired, all the videos were observed using a unique data visualization tool, exclusively developed by the research team to filter out trips that did not occur in adverse weather as can be seen Figure 7.

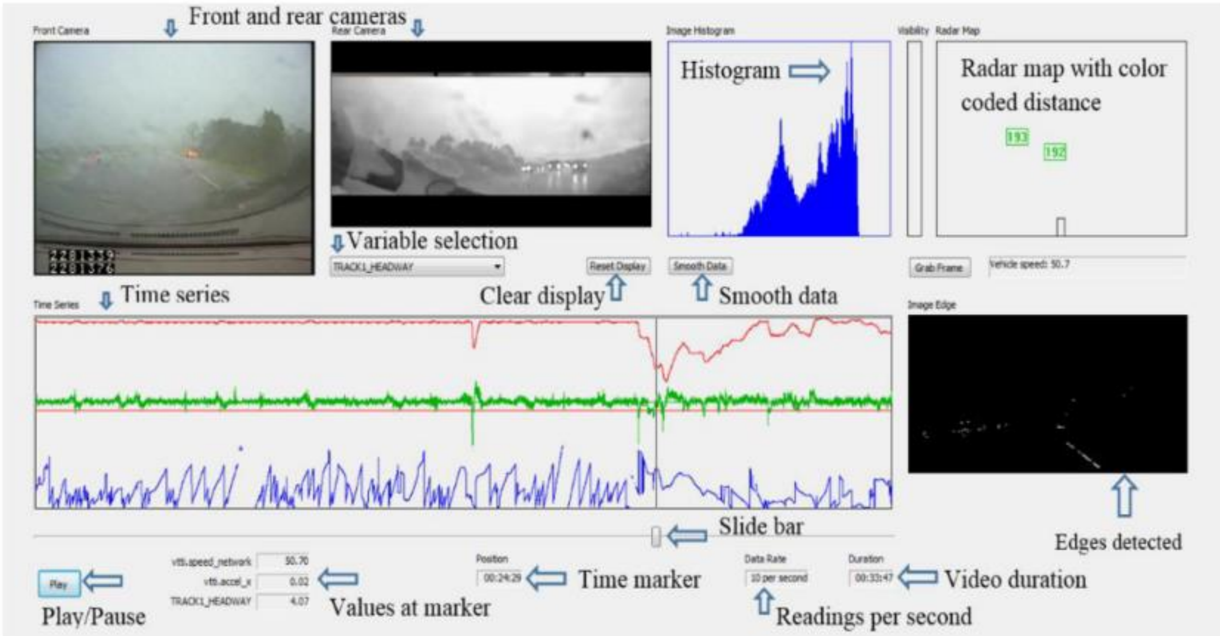


Figure 7: Wyoming Visualization and Visibility Identification Tool (*33*)

Several studies were also conducted by the research team to detect trajectory-level weather conditions at road surface level using the NDS in-vehicle forward video system. For instance, a reliable and cost-effective snow detection system was developed to aid drivers with appropriate information and proper warnings during driving in winter weather. The study utilized the massive SHRP2 NDS video dataset and was based on image processing and machine learning techniques. To train the snow detection models two texture-based image features: GLCM and LBP, and three classification algorithms: SVM, K-NN, and RF, were used. First, a database of images was created from the acquired NDS video data which resulted in a total of 30,000 images. Subsequently, the images were annotated manually and grouped into three categories: clear, light snow, and heavy snow, which were then used to train the machine learning models. The overall prediction accuracies of the SVM, K-NN, and RF models based on the GLCM based features were found to be around 86%, 85%, and 84%, respectively. Subsequently, the same technique was applied considering the LBP based features, which improved the prediction accuracy significantly with overall prediction accuracies of 96%, 93%, and 94% for the SVM, K-NN, and RF models, respectively (*24*).

In addition to the video data and image processing, the research team also used vehicle kinematics to detect real-time weather conditions. In this research, a snow detection system was developed using parameters reduced from a real-time image feature extraction technique, time-series data collected from external sensors, and Controlled Area Network Bus (CANbus) data collected by the NDS vehicles. To provide flexibility in winter maintenance, two segmentation types of one-minute and one-mile segments, were used to sample snowy trips and their matched clear weather trips. In this study, four non-parametric models were developed using six data assemblies to detect snowy weather in freeways. The data assemblies are arranged based on three data sources, including image database extracted from an in-vehicle video camera, sensors, and CANbus data, to examine the effectiveness of snow detection models for different data types considering real-time availability. Overall, the developed models successfully detected snowy weather on freeways with an accuracy ranged between 76% to 89% (35). The research team is currently working on several other weather detection systems using recently developed machine learning techniques, including Deep Learning and Convolutional Neural Network (CNN).

It is worth noting that the developed methodologies discussed in the previous sections were based on only freeways considering the scope of these studies. However, the research team is currently expanding their work to include other roadways, including state highways, as well as urban arterials; and most importantly, the FHWA will apply our methodologies on the entire NDS dataset to increase the value of the SHRP2 data.

3. Study Benefits

In Wyoming, harsh weather conditions such as snow, low visibility due to thick fog, icy road surface, blowing snow and blizzards have resulted in remarkable crashes on the state's highways. The fatality rates are typically higher than the national average, particularly truck-related crashes. Although the negative impact of adverse weather on roadway safety could be reduced by providing drivers with real-time traveler information messages via Intelligent Transportation Systems and other safety countermeasures (such as Advanced Traveler Information Systems, Wyoming 511, Dynamic Massage Signs, and Variable Speed Limits), these systems require accurate real-time road weather information. Nevertheless, existing weather detection systems in Wyoming is mostly based on roadside weather stations, which do not necessarily represent real-time road weather conditions at the surface level.

Although WYDOT operates and maintains a significant number of webcams installed throughout the state and recently implemented an innovative road condition monitoring system using tablets mounted in snow plows and maintenance vehicles, these systems have several limitations. Reviewing and processing images form webcams require significant personnel resources. The monitoring system installed in snow plows and maintenance vehicles require drivers to report weather conditions manually by tapping 9 codes on the tablet touchscreen while driving. The system is using Automatic Vehicle Location (AVL) to link the specific weather code to the actual milepost. Both techniques may result in inaccuracy of reported weather conditions because of the variation of perception of technicians and drivers due to the subjectivity in reporting the different conditions. More importantly, the snow plow manual tracking system may pose some risks to drivers, especially; with their very challenging driving environment during adverse weather conditions. In addition, manual identification of weather by the drivers of the maintenance vehicles and processing this information by the WYDOT TMC personnel to link it to the corresponding road networks are often subjected to human errors and require lots of processing time. On the contrary, the proposed study will automatically collect and extract images from fixed webcams, and will detect real-time weather conditions by using machine learning techniques as well as will linking/ integrating the weather conditions to the corresponding road networks automatically without any human involvement. Therefore, the proposed study will provide more accurate and consistent weather information in real-time that can be made readily available to be used by road users and other transportation practitioners.

The proposed study will help in facilitating and improving maintenance operations and enhance the safety and convenience of highway travel. This will be achieved by addressing the limitations discussed above by developing an automatic weather detection system based on image processing of video recording collected by webcams already installed on numerous locations in the state of Wyoming road network. One of the major benefits of the proposed study is that it will not require any additional camera installations and hence could be an affordable source of collecting accurate weather information in real-time. Furthermore, the weather detection system will be able to provide weather conditions throughout the year, including winter and summer, since it will consider seven levels of weather conditions: clear, light rain, heavy rain, light snow, heavy snow, light fog, and thick fog. It is worth noting that fog, rain, and snow do not usually occur at the same time of the year in the state of Wyoming. Therefore, separate detection models will be developed for winter and summer to eliminate any possible reduction in detection accuracy.

The system will utilize still images collected from IP cameras already installed on highways in Wyoming. An image-based weather detection system using global features combined with machine vision approaches has the ability of overcoming the inconsistency problem. Moreover, a well-trained machine learning model is accurate and cost-effective in determining real-time weather conditions. The automated weather detection system proposed in this research will not require a lot of technical support, and only needs existing video cameras.

The WYDOT Travel Information Service has considered detecting real-time weather conditions and providing drivers with appropriate warnings as the principle task for safe driving under winter weather conditions in Wyoming. In this regard, this study will be crucial for WYDOT to develop more effective traffic management strategies. In addition, the research results will benefit both the scientific community and authorities responsible for traffic safety and decision-making, and will be a key to ensure the least adverse effects of severe weather events on the safety of road users.

The methodology provided in this proposal could be extended to develop other potential future applications to aid in traffic count, vehicle classification, maintenance operations, identification and archiving of work zones, pedestrians, and unexpected incidents, including crashes and road closures. It is worth noting that the implementation costs of a roadside camera unit is relatively low compared to weather stations and traffic count sensors including inductive loop detector (*36*). Therefore, the proposed study has the potential to become an excellent source for not only real-time weather and surface conditions detection, but also traffic volume and classifications on a single hardware platform without including an array of expensive sensors.

4. Statement of Work

4.1 Overview of Research Tasks

Eleven tasks under two phases will be conducted to fulfill the main objective of this study. The primary phase will employ Wyoming Webcam data to detect various weather conditions; then, based on the automatic weather detection algorithm developed in the primary phase, the secondary phase will focus on in-vehicle camera data collected by WYDOT snowplow crew to identify more detailed snow weather events. These tasks are summarized as follows:

Phase I:

1) Conduct a comprehensive literature review of the state-of-the-practice of weather detection and warning systems, and the state-of-the-art of image-based weather detection methodologies;
2) Collect video recordings under various weather conditions from the webcams installed in the Wyoming road networks, extract images from the videos at 10 frames per minute sampling rate;

3) Annotate image dataset describing the classification of weather conditions: clear, light rain, heavy rain, light snow, heavy snow, light fog, and thick fog, and divide the original image dataset to training and validations datasets.
4) Develop automatic real-time weather detection algorithms using various Machine Vision technologies and Artificial Intelligence algorithms;
5) Train the developed weather detection algorithms using the processed video image datasets, and applying the trained algorithms to detect different weather events;
6) Compare the automatically detected weather events with the manually classified ones to validate the accuracy of each algorithm;
7) Develop a system capable of providing time-lapse from a series of image files, develop an index of weather deterioration/improvement, and provide WYDOT a practice-ready automatic weather detection system and a user manual. The detected weather condition will be integrated into WYODT database to evaluate whether WYDOT is actively and accurately reporting the condition. If a condition is not reported correctly, WYDOT developed will send a TRAC message to the TMC to update the report.

Phase II:

8) Acquire video recordings under various snowy weather conditions from WYDOT snow plows; the data will cover different interstate freeways, state highways, as well as urban arterials. This will be done by developing an onboard software using an additional five 10" tablet mounted in snow plows and maintenance vehicles, not to interrupt the normal day to day operation of snow plows;
9) Extract geo-coded still images captured every 0.1-mile from the collected video clips, resize the images, annotate image dataset describing the classification of weather conditions, and divide the original image dataset to training and validations datasets, the captured images will be sent to the TMC and will be posted on WYDOT travel information systems;
10) Repeat tasks 3 to 5 using the snowy weather data collected from snowplows;
11) Provide WYDOT a practice-ready automatic trajectory-level snow detection system and a user manual. The results will be integrated into the WYDOT TMC in the same fashion as discussed in task 7.

An overview of the proposed research tasks and expected products is illustrated in Figure 8 below; detailed descriptions of each task are presented on the following pages.

4.2 Elaboration of Tasks

Task 1: Literature Review

A thorough review of the literature will be carried out regarding the state-of-the-practice on weather detection and traveler information service systems employed by state DOTs in the United States and cities and local authorities throughout the world, and the state-of-the-art of the methodologies used for real-time road weather detection.

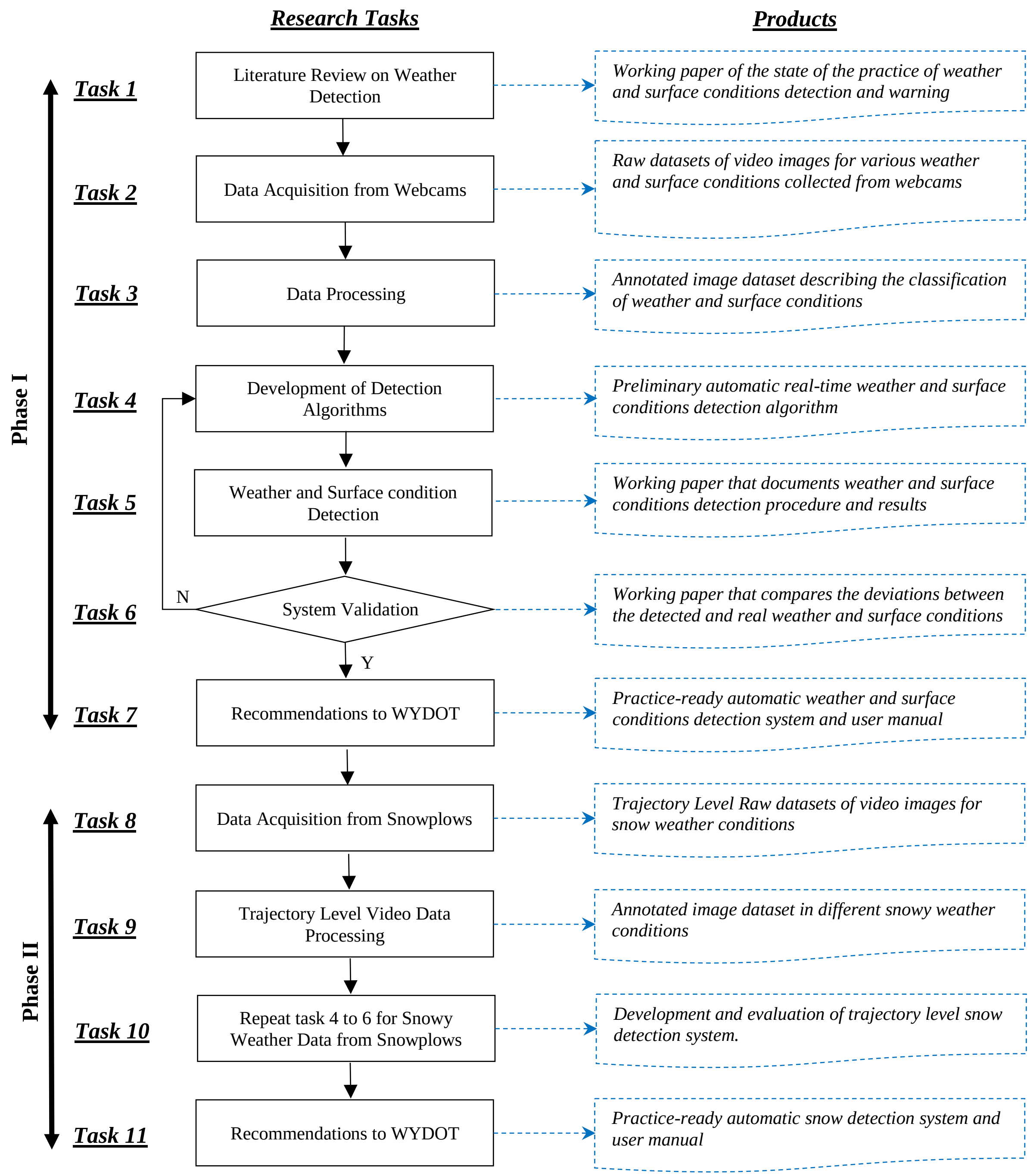


Figure 8. Overview of the Proposed Research Tasks and Expected Products

Task 2: Field Data Acquisition from Webcams

The video data will be collected from the existing webcams installed on the roadways in the state of Wyoming. The collected data will be used for training and validation of the weather and surface conditions detection models. The video data will include different interstate freeways, state highways, and urban arterials. As mentioned earlier, each webcam locations have at least three views of the roadways, including west bound, east bound, and roadway. Therefore, two separate databases will be created for identifying weather conditions and road surface conditions, respectively. The data will be collected for at least one year to ensure enough sample size for each weather condition.

Task 3: Data Processing

After receiving the required video clips, the research team will extract still images from each video clip with ten images per minute sampling rate. The images will be resized to standardized images (i.e., 350 pixels by 250 pixels). Two separate datasets will be created to identify weather and road surface conditions. Then, the research team will develop a matrix which describes the classification of various adverse weather conditions, including clear, light rain, heavy rain, light snow, heavy snow, light fog, and thick fog. In addition, surface conditions will be categorized into six categories: dry, icy, wet, snow-packed, patchy snow, and snow removed. The classification will follow the criteria and guidance recommended by the National Weather Service (NWS) and could be refined depending on WYDOT needs. In addition, a clear weather condition will also be defined as the baseline weather condition. Subsequently, the research team will manually annotate the image dataset to match the classified adverse weather and surface conditions, and divide the original image dataset into a training dataset (80% of the original image data) and a validation dataset (20% of the original image data). The research team will work closely with WYDOT to examine the potential of incorporating the detected weather conditions into Pikalert[1] system. An overview of the procedure for data acquisition and processing is illustrated in Figure 9.

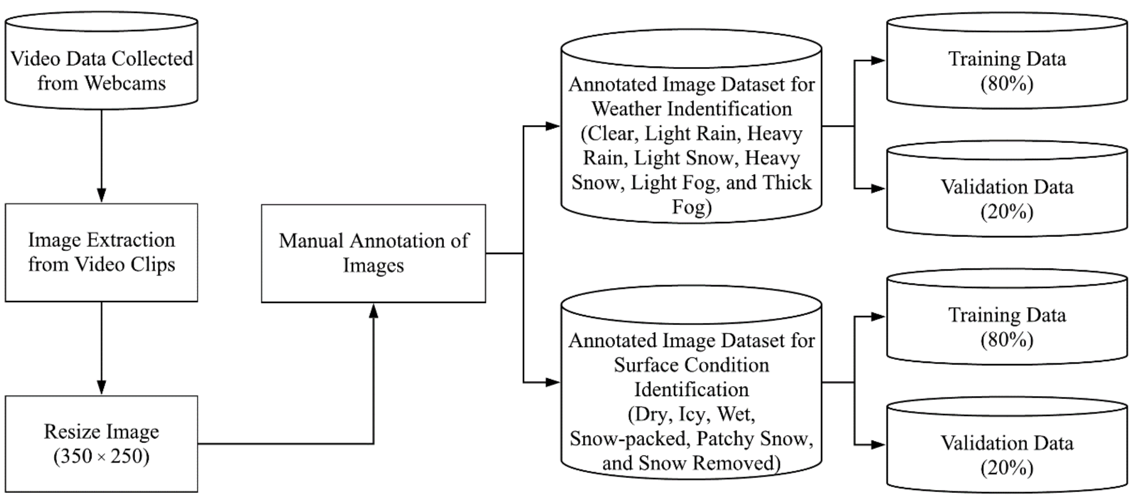


Figure 9. Procedure of Data Acquisition and Processing

Task 4: Development of Machine Learning Algorithms

This task will develop automatic image-based adverse weather detection algorithms using various Machine Vision technologies. To detect adverse weather and surface from the video images, machine-learning technique will be used, which involved the extraction of features from the image datasets followed by training of the extracted feature using different classifiers, and finally testing the accuracy of the trained

[1] Pikalert is a weather detection system developed by the National Center for Atmospheric Research (NCAR), sponsored in part by the Road Weather Management program of the USDOT FHWA. The system is mainly based on weather observations collected form stationary Environmental Sensor Stations. https://www.its.dot.gov/pilots/wydot_pikalert.htm

models using a new test dataset (*24*). In this study, two texture-based feature extraction techniques will be used: Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP). In addition, three classifiers: Support Vector Machine (SVM), k-Nearest Neighbor (K-NN), and Random Forest (RF) will be used on each texture feature separately to classify the image groups. All the computations will be programed and performed using the MATLAB software package on a desktop computer first. The general procedure of the proposed image-based adverse weather detection system is illustrated in Figure 10. To make the system more useful to WYDOT Traffic Management Center (TMC) and make it extendable to the proposed in-vehicle detection system, either python or C language will be used to replicate the process based on the best performing Machine Learning technique, to develop an onboard tablet application. This will reduce the communication requirements of sending too many still images to WYDOT TMC to process and detect weather conditions. The weather detection software will be developed for execution in both Linux OS and Windows. A small footprint single board computers such as Raspberry Pi, NVidia Jetsons, and Xavier with better image processing capabilities could be examined as directed by WYDOT. In this case, the development in Linux OS will be more appropriate.

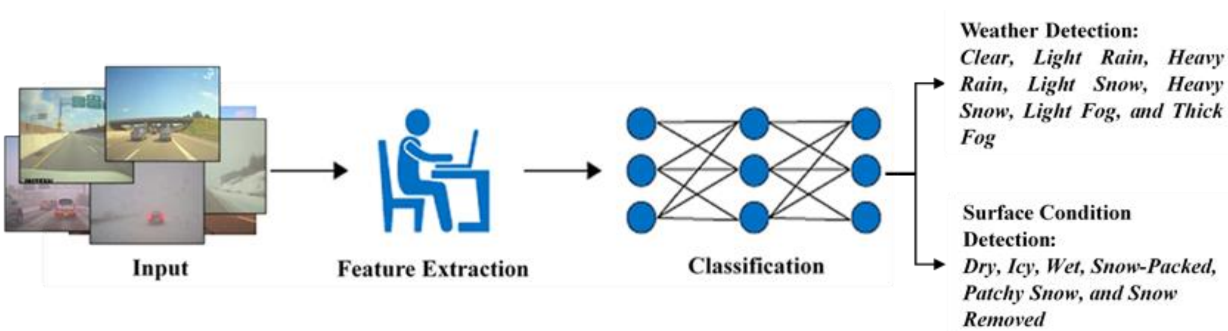


Figure 10. Procedure of Image-based Weather Detection (Source: Khan and Ahmed, 2019)

A brief description of the proposed feature extraction techniques and classification algorithms is presented below:

Feature Extraction Techniques

GLCM is one of the most commonly used approaches for extracting texture features of an image and was developed by Haralick et al. (*31*). GLCM demonstrates how often a pixel value, p (i, j), occurs in an image in a specific relationship with its neighbor pixels. So, each element (i, j) of the matrix is the number of occurrences of the pair of pixels with value i and j.

LBP is a powerful means of texture description which was developed by Ojala et al. (*32*). The LBP operator computes a local representation of texture by comparing each pixel with its surrounding neighborhood of pixels. The original LBP algorithm operates on a fixed 3 × 3 neighborhood of pixels and assigns a level to each pixel of an image. The histogram of the levels can then be used as a texture descriptor.

Classification Algorithms

SVM is a discriminative classifier that is based on finding an optimum hyperplane in a high or infinite-dimensional space. The hyperplane is a line that separates and classifies data into two classes. The distance between the hyperplane and the nearest data point from either side of the hyperplane is known as the margin. The goal of an SVM classifier is to choose an optimum hyperplane with the maximum possible margin between two classes, which provides a greater chance to classify new data correctly (*33*, *34*).

K-NN algorithm classifies a new data point based on a similarity measure, which is defined as distance function. The classification is conducted by a majority vote to its neighbor. The accuracy of the K-NN model might increase with the increase of k value (e.g., the number of nearest neighbors). The choice of k is crucial and considered as one of the most influential factors of prediction quality. A large value of k will introduce large model bias. In contrast, a small value of k will provide large variance in predictions. Therefore, optimum k value should be selected in such a way that provides the appropriate balances between the bias and variance of the model (*35*).

RF is a supervised classification algorithm that makes a set of decision trees from a randomly selected subset of training dataset and aggregates the prediction from each tree using voting (e.g., the prediction provided by each tree) to decide the final prediction. RF usually builds a forest with many classification trees. Typically, large number of trees in RF models provide more accurate predictions. One of the advantages of RF is that it prevents overfitting problem by building trees on random subsets. In addition, it can handle the missing values and provide relative feature importance that helps to select the most contributing feature from the training dataset (*36*).

Task 5: Weather and Surface Conditions Detection

This task will train the developed weather and surface conditions detection algorithms using the annotated training image dataset, and applying the trained algorithms to detect different weather events and surface conditions. The flowchart of using machine-learning technique for snowy weather detection is illustrated in Figure 11.

Task 6: Validation of the Developed Algorithms

After training the GLCM and LBP features using different classifiers, the performance of the trained weather detection algorithms will be tested using the validation dataset. For each algorithm, the validation task will compare the automatically detected adverse weather events with the manually classified adverse weather conditions. This research will employ Positive Rate as an indicator to assess the accuracy of the developed algorithms. Positive Rate refers to the percentage of detected adverse weather conditions that match the annotated adverse weather images in the validation dataset. It is expected that a Positive Rate that is equal or greater than 85% indicates an acceptable detection accuracy. Otherwise, the research team will diagnose the potential issues of the feature extraction and/or classification algorithm(s), re-train the algorithm(s) until the detection accuracy is acceptable.

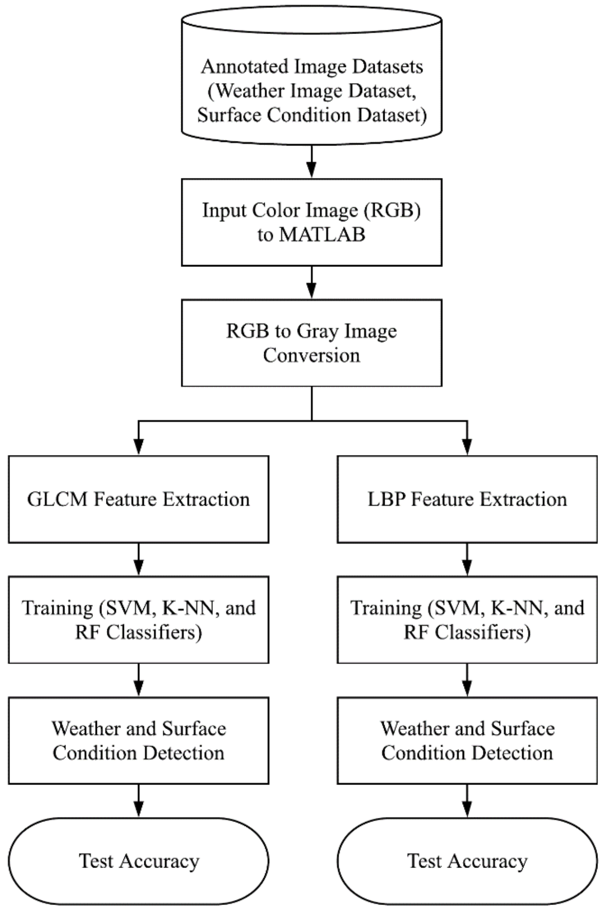


Figure 11. Flowchart of using Machine Learning Technology for Weather and Surface Conditions Detection

Task 7: Recommendations to WYDOT

The final task of the primary phase is to provide WYDOT a practice-ready automated weather detection system using webcams, a mechanism for posting detected weather conditions to a database (working with WYDOT's GIS/ITS development staff) and a comprehensive user manual that details the function and operation of the developed system as well as trouble shooting and solution guidance. Technical support will also be provided upon request. Products of this research are expected to aid in a better recognition of real-time road surface-level adverse weather conditions, and eventually, will benefit WYDOT TMC for more effective transportation management strategies.

Task 8: Data Acquisition from Snowplows

An Android tablet-based application will be developed to collect geolocation video data from WYDOT snow plows and maintenance vehicles. The collected data will be used for training and validation. The video data will include different interstate freeways, state highways, and urban arterials in the state of Wyoming. The Data Acquisition System (DAS) will be developed in a way to ensure effective data collection. It is worth noting that a 512GB SD memory card can store close to 60 days of high resolution video data before it ran out of memory. Since this research aims at detecting high-resolution trajectory-level snowy weather events (i.e., light-, medium-, heavy-snow, and blizzard), for each selected roadway classification, the research team will first identify the intensity of snow storms, and date and time of each snowy weather event; then, acquire video data recorded by WYDOT tablets. Video data for clear weather conditions will be required for training and validation as well. These data will be collected after enough sample size of adverse weather conditions data are collected to ensure effective matching of routes.

Task 9: Trajectory Level Video Data Processing

After receiving the required video clips from WYDOT vehicles, the research team will extract still images from each video clip. The video images will be resized to standardized images (i.e., 350 pixels by 250 pixels). Then, the research team will develop a matrix which describes the classification of various weather conditions, including light snow, medium snow, heavy snow, and blizzards. The classification will follow the criteria and guidance recommended by the National Weather Service (NWS) and could be refined depending on WYDOT needs. For instance, the light snow refers to a condition that snowflakes are visible while do not significantly affect visibility, and little or no snow on the road surface. In comparison, heavy snow means snowflakes significantly affect visibility, road surface is covered with snow and road markings are hardly recognized. In addition, a clear weather condition will also be defined as the baseline weather condition. Subsequently, the research team will manually annotate the image dataset to match the classified snowy weather conditions, and divide the original image dataset into a training dataset (80% of the original image data) and a validation dataset (20% of the original image data).

Task 10: Development and Evaluation of Trajectory-Level Snow Detection System

After the annotation of images, two texture based image features, including GLCM and LBP, will be extracted for each image. Subsequently, three classification algorithms (SVM, K-NN, and RF) will be used to develop the snow detection models using the extracted image features. Finally, the performance of the trained weather detection algorithms will be tested using the validation dataset. For each algorithm, the validation task will compare the automatically detected weather events with the manually classified weather conditions. This research will employ Positive Rate as an indicator to assess the accuracy of the developed algorithms. Positive Rate refers to the percentage of detected weather conditions that match the annotated weather images in the validation dataset. It is expected that a Positive Rate that of equal or greater than 85% indicates an acceptable detection accuracy. Otherwise, the research team will diagnose the potential issues of the feature extraction and/or classification algorithm(s), re-train the algorithm(s) until the detection accuracy is acceptable. Once an acceptable rate is achieved using a specific feature extraction and a classification algorithm, an onboard tablet-based application will be developed using Python. In summary, task 10 will mainly repeat task 4 to task 6 using the trajectory-level video data collected from the snowplows on winter weather conditions.

Task 11: Recommendations to WYDOT

The final task of the secondary phase is to provide WYDOT a practice-ready automated and trajectory level snow detection system using video data collected from snowplows. In addition, the principal investigator will work with WYDOT's GIS/ITS development staff to push the reported conditions to a database, and a comprehensive user manual that details the function and operation of the developed system as well as trouble shooting and solution guidance will also be provided.

5. Work Plan and Implementation Process

5.1 Project Kickoff Meeting

A kick-off meeting shall be scheduled to occur within the first 30 days of execution by the University of Wyoming. The preferred method for the kick-off meeting is via teleconference or video conference. At minimum, the project manager and the principal investigator will attend. The WYDOT Research Center staff must be advised of the meeting and given the option to attend. Other parties may be invited, as appropriate. The subject of the meeting will be to review and discuss the project's tasks, schedule, milestones, deliverables, reporting requirements, and deployment plan. A summary of the kick-off meeting shall be included in the first progress report.

5.2 Deliverables

A prototype weather detection system will be provided to WYDOT. Quarterly progress report will be submitted. In addition, any major achievement, i.e., the completion of tasks will be reported to the project managers. Draft final report and a final report incorporating the project managers' comments and corrections will be submitted at the end of the project.

5.2.1 Progress Reports

The University of Wyoming research team will submit quarterly progress reports to the WYDOT Research Center. The first report will cover the activity that occurred in the 90 days following the issuance of the task work order.

5.2.2 Draft Final Report

The Draft Final Report is due 90 days prior to the end date of the task work order. The draft final report will be submitted to the WYDOT Research Center. It should be edited for technical accuracy, grammar, clarity, organization, and format prior to submission to the WYDOT Research Center for technical approval.

5.2.3 Final Report

Once the draft final report has been approved, the University of Wyoming research team shall prepare the final report. The UW research team will email the final report in PDF as well as MS Word format.

5.2.4 Project Closeout Presentations

The findings of this study will be presented to the WYDOT Research Center at the conclusion of the project.

6. Timeline and Budget

The study will be performed in 24 months after the Notice to Proceed (NTP). The project will be led and supervised by Dr. Ahmed. One postdoctoral associate, and one graduate student will be assigned to different tasks throughout the project. As shown in Table 1, the total cost of the project is $239,733. The total cost will cover all tasks listed above and illustrated in Table 2 including the literature review, travel, hardware and software development, as well as technology transfer. In addition, the total 2 years cost will cover the salaries of one full-time Ph.D. student for 2 years, 4 months salary/ year for one postdoc, and two months salary/ year for one faculty members over the two years. The PI will be submitting a proposal to Mountain-Plains Consortium (MPC) for additional funds for this study as deemed appropriate.

Table 1: *Project Budget*

Budget Years 2019-2021		
Weather Identification using Artificial Intelligence		
CATEGORY	Budgeted Amount from WYDOT	Notes
Faculty Salaries	$19,834	2-month salary for 1 PI
Administrative Staff Salaries	$0	
Other Staff Salaries (Engineers/ Postdocs)	$64,500	Postdoc salary for 1 year / Software Engineer
Student Salaries	$44,760	1 PhD student salary for 2 years
Staff Benefits	$44,289.46	
Total Salaries and Benefits	**$173,383**	
Student Support Other Than Salaries	$19,568	Tuition, 1 PhD student for 2 years/No indirect
Permanent Equipment	$1,500	Tablets/ Storage Media -No indirect
Expendable Property, Supplies, and Services	$1,000	
Domestic Travel	$3,500	
Foreign Travel	$4,000	
Other Direct Costs (specify)	$0	
Total Other Direct Costs	**$29,568**	
F&A (Indirect) Costs	$36,377	20% WYDOT
TOTAL COSTS for 2 Years	**$239,328**	

Table 2: *Project Schedule*

	Research Task	Month																							
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Phase I	**Task 1**																								
	Literature Review	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■						
	Task 2																								
	Field Data Acquisition from Webcams		■	■	■	■	■	■	■	■	■	■	■	■											
	Task 3																								
	Data Processing: Creation of an Annotated Image Dataset							■	■	■	■	■	■	■	■	■									
	Task 4																								
	Development of Machine Learning Algorithms													■	■	■	■	■							
	Task 5																								
	Weather and Surface Detection													■	■	■	■	■	■	■	■				
	Task 6																								
	Validation of the Developed Algorithms															■	■	■	■	■	■				
	Task 7																								
	Recommendations to WYDOT									■	■	■	■						■	■	■	■	■		
Phase II	**Task 8**																								
	Data Acquisition from Snowplows											■	■	■	■	■	■								
	Task 9																								
	Trajectory Level Video Data Processing													■	■	■	■	■	■						
	Task 10																								
	Development and Evaluation of Trajectory Level Snow Detection System													■	■	■	■	■	■	■	■	■			
	Task 11																								
	Recommendations to WYDOT									■	■	■	■							■	■	■	■		
	Documentation and Deliverables Schedule				■			■			■			■			■			■	■			■	■

Quarter Reports   Draft Final Report   Final Report

7. Technology Transfer

The research results will be disseminated through technical paper publications and presentations in academic venues and press releases using media outlets. The technology transfer activities in this project will benefit both the scientific community and authorities responsible for decision-making, and will be a key to ensure the least adverse effects of winter snowy weather events on the safety of drivers.

8. Data Management Plan

A Data Management Plan (DMP) is attached to this proposal. The plan provides a description of the nature, scope, and scale of data that will be collected during the course of the project. The plan provides information on how the data will be collected, shared, where the data will be housed, who will have access to the data, and any backup strategies that will be implemented.

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