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Development of a Salt Spreader Controller Program Using Machine-Sensed Roadway Weather Parameters

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16. Abstract
Massachusetts owns over 300 and contracts 1,200 additional material spreaders that deliver salt, salt, sand mixtures, or liquid deicers to more than 15,000 lane miles of roadways during winter seasons. It is critical to efficiently and effectively deliver the materials so that the impacts of winter storms on road operations are minimized while the utilization of the materials is maximized to reduce potential environmental impacts. MassDOT deploys mobile RWIS sensors (e.g., Vaisala MD30) to better monitor the road surface and ambient weather conditions. This study developed an automated system to optimize material utilization by leveraging mobile RWIS sensors by developing hardware, software, algorithm (road surface condition deep learning algorithm), and model (salt rate prediction model). Based on the experimental results, the newly developed system can potentially save salt applications by approximately 34% and 37%, compared with the auto-grip mode and the manual mode, while maintaining the similar performance of the treatment (i.e., maintaining or improving the grip values).

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Development of a Salt Spreader Controller Program Using Machine-Sensed Roadway Weather Parameters

Final Report

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Disclaimer

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Executive Summary

This study of Development of a Salt Spreader Controller Program Using Machine-Sensed Roadway Weather Parameters was undertaken as part of the Massachusetts Department of Transportation (MassDOT) Research Program. This program is funded by the Federal Highway Administration (FHWA) and State Planning and Research (SPR) funds. Through this program, applied research is conducted on topics of importance to the Commonwealth of Massachusetts transportation agencies.

Winter operation ensures safe and uninterrupted traffic in the Commonwealth of Massachusetts and nationally. Public agencies are actively searching for an optimized "formula" to minimize the utilization of the deicing material without compromising its effectiveness. The study proposed to address this need by leveraging mobile road weather information sensor (RWIS) technologies and automated mechanical controls. If successful, the outcome of this study will include a sensor-based material application decision model and the recommended configurations for sensor instrumentation so that it lays a critical foundation for seamless integration and successful implementation for a more extensive fleet of MassDOT winter operation vehicles in the future.

The research team developed a new salt application system in this study by leveraging the instrumented mobile RWIS (i.e., Vaisala MD30 sensor), computer vision, and a new salt application model. The research team focused on developing four key aspects of the intelligent salt application system, including hardware (i.e., data collection I/O and power supplies system), software (i.e., data logging, synchronization, and data fusion), algorithm [i.e., road surface classification (RSC) algorithm], and model [i.e., the salt rate prediction (SRP) model], so that an optimized salt application decision can be provided to the actuator to treat the road surfaces. Through this study, a complete hardware/software system with automated RSC and SRP algorithms has been developed, pilot-tested, and validated with promising performance.

Experimental tests during winter weather events facilitated an analysis of the salt rate prediction model and an evaluation of the efficiency of auto-grip mode, manual mode, and a salt treatment mode, which uses rates recommended by the salt rate prediction model. Further analysis was performed using simulation under fixed weather conditions. A comparative analysis of the results derived from all experiments was performed based on grip improvement and salt usage. The salt rate prediction model outperformed both auto-grip mode and manual mode.

- The research team explored the full integration feasibility of mobile RWIS sensors, high-resolution cameras, GPS, and Geotab logger and developed prototype software for comprehensive data collection.
- The research team developed an automated road surface classification algorithm using the DenseNet121 deep-learning model with an 86.7% accuracy.

- The research team integrated the detailed road surface classification outcome, the key parameters from the mobile RWIS sensor with a comprehensive salt rate decision tree that can potentially save salt applications by approximately 34% and 37%, compared with the auto-grip mode and the manual mode, while maintaining the similar performance of the treatment (i.e., maintaining or improving the grip values). The performance of the developed system showed promising results and could potentially save a significant amount of salt once implemented in a larger fleet of MassDOT's winter operations.

The salt rate prediction model simulation revealed an approximately 18% decrease in salt usage compared to auto-grip mode. The salt rate prediction model demonstrated efficient performance through cumulative results analysis, particularly during use under moderate to heavy weather conditions and sleet mixed snow weather conditions.

For future studies, the RSC model's capabilities should be enhanced to improve the salt rate prediction model further. More road condition categories (e.g., black ice and packed snow) and more road image examples could be considered. The RSC model's functionality should also be extended to consider nighttime road condition identification for nighttime salt treatment. Additional factors such as surface temperature gradient (increasing or decreasing) and the type of winter storm events anticipated, including light, medium, and heavy snow, sleet, black ice, or freezing rain, should be considered to further improve the overall performance of salt treatment. These factors can significantly impact the salt rate required for effective road treatment. They should be considered alongside surface grip, road condition, and surface temperature when determining the appropriate salt rate.

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List of Acronyms

Acronym	Expansion
ANN	Artificial Neural Network
AP	Average Precision
AUC	Area Under Curve
CNN	Convolutional Neural Network
CSV	Comma-Separated Values
DOT	Department of Transportation
ESS	Environmental Sensor Station
FHWA	Federal Highway Administration
GPS	Global Positioning System
GUI	Graphical User Interface
IMU	Inertial Measurement Unit
LCD	Liquid Crystal Display
LDL	Local Data Logger
mAP	Mean Average Precision
MassDOT	Massachusetts Department of Transportation
PR	Precision–recall
RGB	Red, Green, Blue
ROC	Receiver Operating Characteristics
RSC	Road Surface Condition
RWIS	Road Weather Information System
SPR	State Planning and Research
SRP	Salt Rate Prediction
USB	Universal Serial Bus
VAMS	Value Added Meteorological Services
WRTM	Weather Responsive Traffic Management

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1.0 Introduction

This study of Development of a Salt Spreader Controller Program Using Machine-Sensed Roadway Weather Parameters was undertaken as part of the Massachusetts Department of Transportation (MassDOT) Research Program. This program is funded by the Federal Highway Administration (FHWA) and State Planning and Research (SPR) funds. Through this program, applied research is conducted on topics of importance to the Commonwealth of Massachusetts transportation agencies.

Winter operation plays an indispensable role in ensuring safe and uninterrupted traffic in the Commonwealth of Massachusetts and nationally. Public agencies are actively searching for an optimized "formula" to minimize the utilization of the deicing material without compromising its effectiveness. The study proposed to address this need by leveraging mobile road weather information system (RWIS) technologies and automated mechanical controls. If successful, the outcome of this study will include a sensor-based material application decision model and the recommended configurations for sensor instrumentation so that it lays a critical foundation for seamless integration and successful implementation for a more extensive fleet of MassDOT winter operation vehicles in the future.

1.1 Background

Winter weather conditions concern many practitioners as the driving environment changes, leading to potential risks for road users. Several aspects of the driving task change due to visibility issues and decreasing stopping distances. Some instances of snow may cause lane markings to be obstructed, potentially leading to disorderly driving in some instances. Considering that around 70% of US roads are in potentially snowy regions, planning for salt deployments becomes vital (*1*). According to the US Department of Transportation, on a yearly average between 2007 and 2016, 688 fatalities occur during snow or sleet, 521 fatalities occur during icy pavement conditions, and 496 fatalities occur during snow or slushy pavement conditions. In addition to safety concerns, transportation networks may be hindered due to capacity issues emerging from obstructed lane markings or the reduced speeds of all road users. Looking at costs associated with delays from weather-related events, trucking companies or commercial vehicle operators incur around 2.2 to 3.5 billion dollars. For weather overall, 23% of non-recurrent delays are also due to snow, ice, and fog conditions. To combat safety concerns and delays due to snow and ice, around 2.3 billion dollars are spent yearly by state and local agencies (*2*). Safety concerns, delays, and costs could be mitigated by optimizing road treatment strategies, such as determining when and where to deploy snow treatments.

To better understand how treatment plans operate, the risks and driver behaviors surrounding winter events may also be important to understand. Driver behaviors during winter storm events tend to change to accommodate the increased risk of snow-related accidents. It means drivers tend to decrease other risk factors when driving through snow, potentially meaning that accidents occurring during snowy or icy conditions may be due more to the environment than to human factors due to driver behaviors. It can be seen in the decreased speeds during snowy or icy conditions. Also, fatality reports from snowy or icy conditions have less alcohol or drug use involved, as well as fewer cases or no seat belts being used, indicating that drivers may be trying to mitigate their potential risks. Looking at the rate of crashes, variations appear across the country due to different levels of exposure, where states like Alaska, with higher chances of icy roads, have more weather-related fatality rates when compared to other states like Arizona, with less exposure to rain and snow. Adverse weather conditions on rural roads may result in higher fatality rates than in other areas (*3*). In the case of South Carolina and North Carolina, the crash risks for both states differ during winter storm events, where North Carolina increases more than when compared to South Carolina. Time of day can also factor in driver risk, where, due to demand, weather-related crash risks during daylight hours may be higher than at night (*4*). Crashes during winter weather may be related more to the changes in the environment than to individual drivers, where the presence of snow overall increases the risk of incidents for drivers.

According to an FHWA study, US snow and ice removal costs exceed $4 billion annually (*5*). Therefore, public transportation agencies are actively searching for best practices for winter operations through effective salt and deicing material application and efficient snow and ice removal using salt spreading machinery (i.e., salt spreader).

The use of salt spreaders is, in general, based on weather conditions. Accurate weather information is needed before the salt spreader operation. This information includes the type of expected snowfall (e.g., light, moderate, and heavy). In addition, a rain prediction is often needed in conjunction with a snowy weather event. If rain is expected before snowfall, applying deicing material on the pavement is not advisable since it can wash away the deicing material, rendering it ineffective. Pavement temperature and condition play significant roles in determining the type and application rate of deicing material. Guidelines published by the US Department of Transportation FHWA (*6*) specify the appropriate application rates for different deicing materials. It specifies deicing material application rates based on pavement temperature range, trend, and pavement surface condition. These rates are adjusted according to different weather conditions. Anti-icing strategies involve operational, decision-making, and personal toolboxes. The operational toolbox includes decisions regarding applying solid or liquid chemicals and plowing.

A crucial element of a typical system is a road weather information system (RWIS), which provides essential weather data that could guide timely winter operations. Such a system collects weather information such as temperature, wind speed, and precipitation. Traditionally, stationary RWIS provides general weather information for winter operations, especially planning. In recent years, mobile RWIS has become more frequently used to provide real-time information about the local weather and road surface conditions (e.g., surface temperature, grip levels, etc.). The operator can assert manual control of a salt spreader by utilizing the data obtained from mobile RWIS, predetermined guidelines, and visual observations. The driver adjusts the spreader's flow rate, speed, and direction to ensure efficient and accurate salt distribution on the road surface. However, the manual control of the spreaders also means potential distractions from driving. Moreover, the effectiveness of leveraging these pieces of road surface information was not quantitatively evaluated. Therefore, public transportation agencies also search for best practices and optimized systems to integrate such important information.

1.2 Problem Statement

Massachusetts owns over 1,300 material spreaders that deliver salt, salt and sand mixtures, and liquid deicers to more than 15,000 lane miles (*7*) of the Commonwealth's roadways during winter seasons. Typically, 600,000 tons of salt and 1.6 million gallons of liquid deicer are used for snow removal operations in Massachusetts (*8*). Delivering the materials efficiently and effectively is critical to minimize the impacts of winter storms on road operations. In contrast, using the materials is maximized to reduce potential environmental impacts. In current operation, MassDOT primarily utilizes spreader controllers manufactured by Certified Cirus (SpreadSmartRx systems) and Bosch Rexroth (Compu-spread systems). Traditionally, it is often challenging for equipment operators to judge the surface condition (e.g., just moist, starting to glaze, etc.) and adjust the spreader accordingly. MassDOT deploys mobile RWIS sensors (e.g., Vaisala MD30) to better monitor the road surface and ambient weather conditions. The mobile RWIS sensors have been installed primarily in supervisor vehicles and on a District 3 material spreader.

RWIS units are introduced to help a supervisor/plow driver assess actual conditions, including road temperature, grip level, and surface state, so that the operations can decide whether to withhold or distribute deicing materials and at which rate to distribute the materials. The introduction of the RWIS sensor is anticipated to improve the supervisor/plow driver's assessment of the road conditions and help him make informed decisions. However, reading RWIS measurements remains manual, demanding the supervisor/plow driver's constant attention to the display. Consequently, it may cause the supervisor/plow driver to miss the optimal window for adjusting the controller. There is a need for an automated system that integrates the RWIS sensory output (i.e., road temperature, grip level, and surface state), determines if the sensory output indicates a local need for roadway deicer treatment, and automatically interacts with the spreader controller to control and dictate the material distribution rate based on the locally observed roadway conditions.

1.3 Objectives

An automated system for salt distribution based on pavement conditions was developed to address the identified issues and create an effective system for intelligently delivering deicing materials by leveraging the existing instrumentation of Vaisala MD30 mobile RWIS sensors. This system determines the salt rate based on environmental parameters from the MD30 sensor and road conditions from a camera. By incorporating this data-driven approach, the system can deliver a salt distribution rate tailored to the specific pavement conditions, with improved deicing effectiveness while minimizing salt waste. The following are the three key research objectives:

- To identify parameters and factors that influence the salt rate. The current MassDOT practice relies solely on grip or temperature values and operator judgment.
- To develop a computer vision/machine learning model that can accurately identify road surface conditions (e.g., dry, wet, slushy, streaming water, snowy, and snow-covered with wheel tracks) eventually to eliminate the need for visual monitoring and subjective analysis of road surface conditions.
- To develop an intelligent algorithm that holistically considers the derived road conditions (from the computer vision model) and the real-time RWIS measurements (from the MD30 sensor) and generates the optimized salt rate values specific to road conditions and environmental parameters. The algorithm will alleviate the need for operators to constantly provide on-road assistance in comprehending road and environmental conditions and determining the appropriate salt distribution rate.

2.0 Research Methodology

The research methodology for this study consisted of three main parts: a review of existing data and technologies, collection of the mobile LiDAR data, and processing of the mobile LiDAR data for pedestrian infrastructure inventory. Section 2.1 summarizes the key findings and insights from the literature review that can be applied to make informed decisions regarding salt application rates and leverage existing advancements in road surface recognition. Section 2.2 presents an overview of the research methodology, followed by Sections 2.3 through 2.6, which describe the new system's development of hardware, software, and algorithms.

2.1 Literature Review

This section begins by discussing the existing automation features in current salt spreader systems, providing an overview of the advancements made in this area and identifying potential areas for improvement in line with the research objective, followed by an exploration of the key weather parameters that play a critical role in determining the salt distribution rate. It examines how the combination of these weather parameters influences the application rate of salt. The subsequent subsections focus on the state-of-the-art approaches in winter operation, specifically using machine learning models for road surface recognition.

2.1.1 Adverse Winter Weather Maintenance Strategies

Several strategies across the country may have been adopted to reduce the risks of adverse winter weather. Strategies can be summarized as combining three types: advisory, control, and treatment (*9*, *10*). Advisory strategies would function by letting the public know of potential weather concerns through multiple channels, such as dynamic message signs on roads, 511 traffic systems that would allow drivers to know of road conditions in advance, mass notification systems, or other channels that would allow the public to be notified.

Control strategies would be in the form of limiting what drivers can do. Typical strategies may be to not permit some types of vehicles on certain roads or to limit travel to vehicles with only proper weather preparations. It can be seen in past winter storm events, where sections of the interstate had restrictions imposed before a winter storm event to allow winter weather treatments to begin. Pennsylvania has used such restrictions, where different travel restrictions have been imposed on interstates to allow maintenance crews to prepare roads (*11*). Other control methods could also be explored, such as manipulating signal timings of intersections (*9*). For traffic signal timings, studies have collected historical traffic flow data at signalized intersections from past weather events to determine new signal timings for future weather events (*12*). Practitioners also need to determine what thresholds need to be reached to activate these alternative signal timings by considering the severity, duration, speed, start-up lost time, and other factors that may be relevant to different locations. Winter weather signal timings could accommodate for changed driver behaviors, such as extending yellow times or all red times to ensure intersections are clear. It would account for decreased speeds and increased braking distances, giving drivers enough time and notice to fully brake and clear an intersection due to slower turning movements (*13*).

For treatment, strategies can be in the form of road maintenance or by automatic means. Road maintenance can be in the form of anti-icing and deicing. Anti-icing prevents snow and ice from attaching to pavements while decreasing the temperature at which ice forms. Deicing would involve removing the ice from roads through plows or deicing materials such as rock salt. Deicing is also completed after snowstorms, as roads may become icy afterward (*14*). Automatic deicing infrastructure has been used in areas that may expect heavy delays due to icy roads. One example would be bridges, where sensors detecting wet weather and freezing temperatures trigger automatic anti-icing solutions to prevent bridges from facing potential delays due to ice (*15*). These bridges may be armed with stationary Environmental Sensor Stations (ESS), which capture information on wind conditions, precipitation, temperature, inches of snow present, road surface conditions, and various other data types (*16*), which can be used to decide if weather conditions merit anti-icing treatments. These stations also tie into stationary RWIS as a means of data collection on weather conditions to inform decision-making around adverse weather conditions.

2.1.2 Salt Deployment Guidelines

For treatment strategies, salt deployment guidelines have been outlined by FHWA, where the thresholds to be used for different application rates and the type of anti-icing or deicing to use are outlined. The guidelines consider the type of winter storm, pavement temperature, pavement surface conditions, and what part of the winter operations are being considered. The types of winter storm events used are light snowstorms, moderate snowstorms, heavy snowstorms, or a mix of the types. Light snowstorms would be considered when snow is under 12 mm per hour, while snow above 12 mm per hour can be considered heavy. The pavement and temperature trends have varying temperature thresholds for different application rates. The pavement surface cover considers dry, wet, slush, or light snowfall conditions. The material application rates also change depending on whether this was the initial operation (anti-icing) or subsequent operations (deicing). It is summarized in Table 2-1 (*6*). Variations of this table can be seen in other winter storm operations planning, such as with the Arizona Highway State Operations manual, which goes into more specifics about the type of winter storm event being delt with, such as freezing rainstorms, sleet storms, and black ice. A trend seen in the FHWA and Arizona operations is that material does not need to be deployed when temperatures are steadily above 32°F, rising above 32°F, or where temperature is below 15°F steadily or falling. Below 15°F, salt applications are not used as the materials reactions are slowed (*17*).

Table 2-1: Sodium chloride (NaCl) application rates outlined by FHWA

Winter Storm Event	Pavement Temperature and Trend	Pavement Surface*	Initial Operation (anti-icing) Sodium chloride (NaCl) spread rate		Subsequent Operations (deicing) Sodium chloride (NaCl) spread rate	
			Liquid (gal/ lane-mi)	Solid or Prewetted Solid (lb/ lane-mi)	Liquid (gal/ lane-mi)	Solid or Prewetted Solid (lb/ lane-mi)
Light snowstorm	Above 32°F steady or rising	D/W/S/LS	—	—	—	—
	20 to 32°F	D	28 (100)	28 (100)	28 (100)	28 (100)
	20 to 32°F	D/W/S/LS	28 (100)	28 (100)	28 (100)	—
	15 to 20°F	D/W/S/LS	—	55 (200)	—	55 (200)
	Below 15°F	D/W/S/LS	—	—	—	—
Light snowstorm w/period(s) of moderate or heavy snow	Above 32°F steady or rising	D	—	—	—	—
	25 to 32°F	D	28 (100)	28 (100)	55 (200)	55 (200)
	25 to 32°F	D/W/S/LS	28 (100)	28 (100)	55 (200)	—
	15 to 25°F	D/W/S/LS	—	55 (200)	—	55 (200)
	Below 15°F	D/LS	—	—	—	—
Moderate or heavy snowstorms	Above 32°F steady or rising	D	—	—	—	—
	30 to 32°F	D	28 (100)	28 (100)	28 (100)	28 (100)
	30 to 32°F	W/S/LS	28 (100)	28 (100)	28 (100)	28 (100)
	25 to 30°F	D	55 (200)	42–55 (150–200)	55 (200)	55 (200)
	25 to 30°F	D/W/S/LS	55 (200)	42–55 (150–200)	55 (200)	55 (200)
	15 to 25°F	D/W/S/LS	—	55 (200)	—	70 (250)
	Below 15°F	W/S/LS	—	—	—	—

* D-Dry; W-Wet; S-Slush; LS-light snow cover

In Michigan, other factors like dew points and humidity are considered. A flowchart was outlined to determine if anti-icing material is necessary during incoming snow events (Figure 2-1**)** (*18*). Variations in deployments between different areas can also be attributed to differing geographical locations, where other local factors must be considered. However, common factors appearing across guidelines consider the type of winter storm, pavement temperature, and pavement surface condition, as outlined by the FHWA. At the same time, some add their variations and other factors to consider.

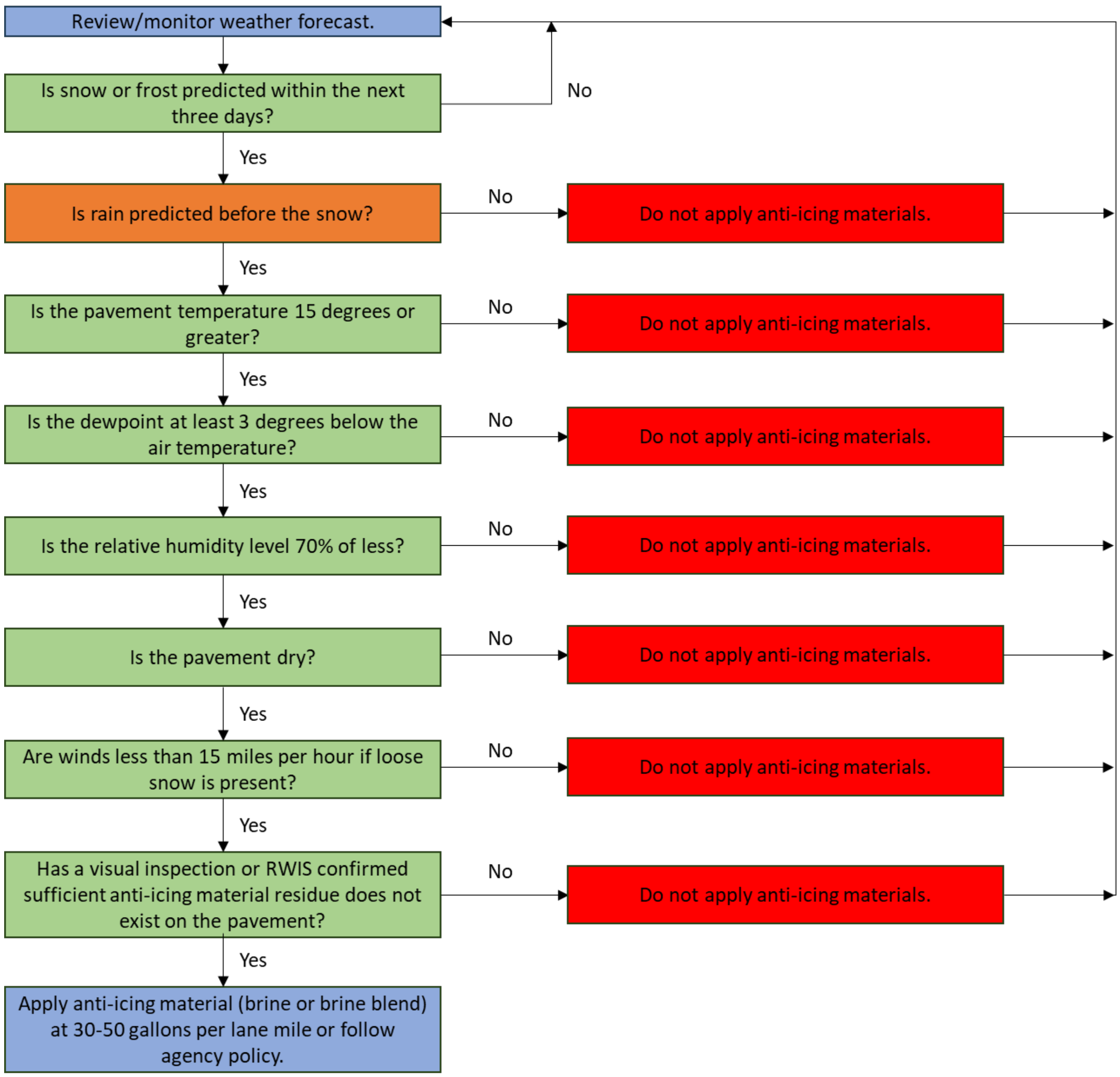


Figure 2-1: Flowchart for anti-icing decisions from Michigan

2.1.3 Road Weather Information System (RWIS)

An RWIS can be used to inform winter operations and set guidelines. A typical RWIS uses ESS, which allows for the communication of data from sensors on an ESS to summarize atmospheric, pavement, and potential water level conditions. An RWIS can be used with observations from sources like the National Weather Service or private vendors referred to as Value Added Meteorological Services (VAMS). Some DOTs have also used snowplows with sensors to deliver mobile data on pavement conditions (*19*). Using RWIS systems allows for optimizing the strategies practitioners have available to them, allowing for dynamic responses to weather events as they occur. Considering that winter weather may not be universal across the United States, dynamic approaches enabled by an

RWIS can help optimize winter maintenance with location-specific data. Nevada DOT has used an RWIS to adapt its response to incoming winter storms to dynamically determine the distribution of anti-ice solutions before a storm. By optimizing its treatments, Nevada DOT also reduced its environmental impacts on some of the lakes surrounding its roads (*20*). In the case of Georgia DOT, by using multiple locations for RWIS data collection, they have the potential to minimize their pre-treatment material usage to match with the smaller winter storms they tend to have, with some cases potentially removing the need for post-treatments like applying more rock salt (*21*). Minnesota DOT can efficiently deploy anti-icing solutions by using an RWIS for forecasts of ice in an area, resulting in less ice presence in many of their areas and minimizing the environmental impact of deicing treatments (*22*).

Traditionally, an RWIS is stationery. It creates a limitation for a RWIS, where there is no complete coverage of road networks because of its fixed location. For this reason, mobile RWISs are being explored to better represent road conditions during adverse weather conditions. The collected mobile data also needs to be communicated to decision-makers. It can be done through what the Federal Highway Administration outlines as Connected Vehicle-enabled Weather Responsive Traffic Management (WRTM), where data can be collected through three pathways. Intelligent agency fleets can mobilize agency-owned vehicles with sensors and deliver collected data through cellular networks, radio, or other means owned or available to the operating agency. Connected vehicles could also be used to connect data and information to public agency vehicles, private vehicles, and infrastructure over dedicated short-range communications. A final alternative would be to outsource data collection to private companies with the infrastructure ready to collect and communicate collected information to any DOT (*23*). This data communication could be a potential obstacle to a DOT, depending on whether the infrastructure to send and receive the collected mobile data can be established.

The sensor model used may also be important when considering mobile RWIS. There may be sensor-specific methods of communicating data, such as Bluetooth, Wi-Fi, or cellular networks, which may be an issue for some. Although some sensors may have similar performance levels, they may have unique aspects that make some better. The performance of mobile RWIS sensors has also been reliable, with studies reporting friction estimates measurements as high as 93.3% (*24*, *25*), indicating that icy roads can be accurately identified. Some sensors may measure additional properties beyond those needed for estimating friction. However, these additional properties may be unnecessary for some. The means of mounting the sensor can also be a limitation depending on the use case of practitioners, where some sensors may come with restrictions on where they can be mounted, such as height or location on a vehicle (*25*).

Mobile RWIS deployments have not been widespread, with some states considering their potential use and only a few having tested them. Mobile deployments have been explored for Colorado, Indiana, Michigan, and Minnesota. Colorado, Indiana, and Michigan are among the top 10 states with the most snow, which may help merit using a mobile RWIS. These states presented information on their experience with a mobile RWIS, such as challenges faced and outcomes. These states identified challenges around installations, operations, and personnel for their mobile RWIS, weather forecast, and road maintenance tool. For the mobile RWIS, some states had operational challenges in that wires may have been damaged (due to corrosion) during data collection. Some personnel challenges emerged in that some were disinterested or resistant to changes. Installation problems emerged for some states with the maintenance decision tools being used, where some had issues with the interface and data feeds of the program being used on setup. Operational challenges emerged where not everyone had access to data or data was being modified before release. Personnel challenges emerged from the level of interest and issues in trusting the forecast output from their forecast tools. Users of the collected data also varied between states. Some had their maintenance decision tool feed information to snowplow operators to advise them on what to do during maintenance operations. Some also had data used on traveler information systems. Colorado DOT had also commented how the potential benefits from the low costs of a mobile RWIS sensor might also pale compared to the costs of a snowplow, making data collection a valid approach to take as plows are already on the move (*26*).

Regarding the benefits of using a mobile RWIS, some states report savings in material costs due to optimized decision-making. For Colorado and Minnesota, both states saw decreases in material usage, with Minnesota reporting it had saved about $2,308,866. Maintenance decision tools and mobile RWISs used by some states also had operational costs to consider, such as the parts and devices needed to implement the system being used, overhead costs such as those related to maintaining collected data as well as the programs being used, implementation costs to develop the necessary infrastructure. Another benefit that Colorado had seen was that the results from the maintenance decision tools also served as training for new plow operators. Michigan also reported that it helped locate what areas may have potential manpower shortages based on the forecasts reported by maintenance decision tools (*26*).

2.1.4 Existing Salt Deployment Systems

Different salt deployment systems use a mix of solutions. Some involved using input sensors on a vehicle to automatically adjust salt deployment patterns and quantities based on lookup table values as thresholds are reached from sensors. Some also use collected spatially defined sensor data before a storm to change the configuration of salt spreaders to be used during the storm. Some deployments also use feedback sensors to adjust their configurations based on a mix of measured and signaled salt spreading to adjust salt deployment.

The EpoMaster X1 and SpreadSmartRx salt spreader systems use sensors of various types to control salt deployment rates, patterns, and mixtures in conjunction with lookup tables to determine what pre-made configurations to use. Pavement temperature sensors, for instance, tend to be used as the main parameter controlling deicing fluid deployment. Other types of sensors, such as ground speed sensors, can help adjust the salt deployment rate to mitigate excessive deployment at low speeds during vehicle stops or match higher vehicle speeds (*27*, *28*).The SpreadSmartRx system, in particular, uses the temperature sensor to determine the quantity and salt type based on preset temperature thresholds sensed. This system uses feedback sensors to measure material output compared to signalized output to make real-time adjustments to deployments, maximizing material efficiency (*28*).

The AEBI Schmidt system also uses a GPS device while trucks are on deployment to make a spatially defined salt spreading scheme. A truck collects data before a storm with its GPS to develop a salt-spreading plan enacted while the truck is on deployment. The truck still uses GPS and has a known location, which dictates the configuration. This system also adjusts spread rates based on vehicle speeds by combining this with other sensors like ground speed sensors. Salt spreading can also be based on observed surface conditions and pavement temperatures instead, where data is fed from controller screens, sensors based on road surface detection, or fixed RWIS systems (*6*, *17*, *18*). These road conditions could also be obtained using cameras with machine learning algorithms (*29*, *30*).

2.1.5 Image Processing to Extract Road Conditions

Some subjective factors have been needed for the guidelines outlined to determine what salt spreading patterns, application rates, and mixtures to use. This would be a point of inefficiency as more labor and time are required to efficiently deploy salt if subjective measures are required. For instance, pavement surface conditions may prove to be difficult to measure directly without the presence of dedicated sensors requiring subjective evaluations. To this purpose, convolutional neural networks (CNNs) can be useful for automatically classifying road surface images, which can be done through smartphones (*30*). The application of image processing can further improve existing salt deployment systems.

A CNN performs better with higher quantities and varying images to be trained on. Using road surface conditions (RSC), images for training features common to different conditions can be extracted for future predictions. Different classification sizes at 2, 3, and 5 can be used to evaluate pavement surface conditions. In a binary classification, RSCs can be classified as bare or snow-covered. In a three-class description, classes could be bare, partly snow-covered, or fully snow-covered. In a five-class description, road surfaces can be bare snow, with the different quartiles of coverage being 0 to 25% snow covered, 25% to 50% snow covered, 50% to 75% snow covered, and 75% to 100% snow covered. A past study testing these classification schemes has found that the binary classification has the highest accuracy at 90.7% (*30*).

Past studies have also tested pre-trained CNN architectures in terms of their accuracy in classifying weather detections and surface conditions. Images collected from roadside webcams on an interstate were separated into two separate data sets. One consisted of 15,000 images annotated based on surface conditions in dry, snowy, or wet/slushy categories. Another 3,000 images were annotated for weather detection, being clear, light snow, and heavy snow. Using these data sets with the CNN architectures, AlexNet (*31*), GoogLeNet (*32*), and ResNet18 (*33*) showed that ResNet18 had the best performance, with 99% accuracy in evaluating surface conditions and 97% accuracy for weather detection (*29*).

2.1.6 Summary

Using RWIS can be useful in enhancing existing winter weather maintenance strategies. The information collected can be shared with the public for advisory strategies. An RWIS, when used to determine forecast and treatment plans, can also help with control strategies, as roads requiring closures or restrictions could be better identified. It can be especially useful in treatment strategies by helping to optimize treatment strategies, reducing the amount of material used, and potential environmental impacts. More optimizations can be completed by expanding on stationary RWISs with mobile RWISs. A stationary RWIS would not completely represent what road conditions are like. However, using a mobile RWIS, road conditions can be collected and dynamically responded to. It allows for more refined data, further improving maintenance and treatment strategies. Some considerations to make with implementing a mobile RWIS would be to explore the system’s different requirements, such as what sensor to use, how data would be communicated, how to interpret the data, and who would have access to the data afterward. Another consideration could also be how applicable machine learning methods may be to the currently available systems and deployments as methods of increasing efficiency through automation. Because of the costs associated with implementing this type of system, states with higher snowfall could benefit more from a mobile RWIS as these states face higher risks around winter weather. Considering the amount of deicing and anti-ice materials used by snowy states, optimizing their use may lead to material cost reductions, leading to greater benefits for states using more materials like what was seen with Minnesota. A mobile RWIS allows for cost savings and reduces environmental impacts and potential risks drivers may face.

2.2 Methodology Overview

The research team developed a new salt application system in this study by leveraging the instrumented mobile RWIS (i.e., Vaisala MD30 sensor), computer vision, and a new salt application model. Figure 2-2 illustrates the high-level block diagram of the developed intelligent salt application system. The research team focused on developing four key aspects of the intelligent salt application system, including hardware (i.e., data collection I/O and power supplies system), software (i.e., data logging, synchronization, and data fusion), algorithm (i.e., RSC algorithm), and model (i.e., the SRP model), so that an optimized salt application decision can be provided to the actuator to treat the road surfaces. In Sections 2.3 through 2.6, the details of the design and implementation of these aspects of the system are presented, respectively.

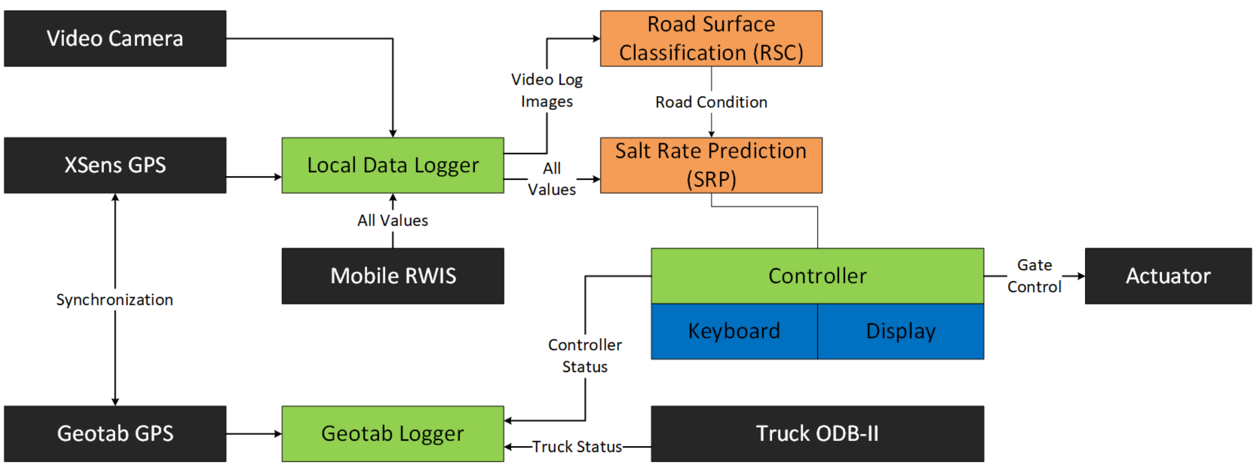


Figure 2-2: High-level block diagram of salt spreader system

2.3 Intelligent Salt Application System: Hardware

2.3.1 Existing Hardware on Trucks at MassDOT

As described previously, MassDOT uses the Vaisala MD30, a mobile RWIS sensor, in snowplows to gather real-time environmental and road surface data. A SpreadSmartRx controller effectively manages the salt rate and spreading pattern based on the reported data from the MD30 sensor. In addition to the mobile RWIS sensor, the instrumented vehicle in MassDOT has also been equipped with the Geotab data logger to record all the vehicle and spreader controller's status information. Figure 2-3 illustrates the system that MassDOT has instrumented on trucks.

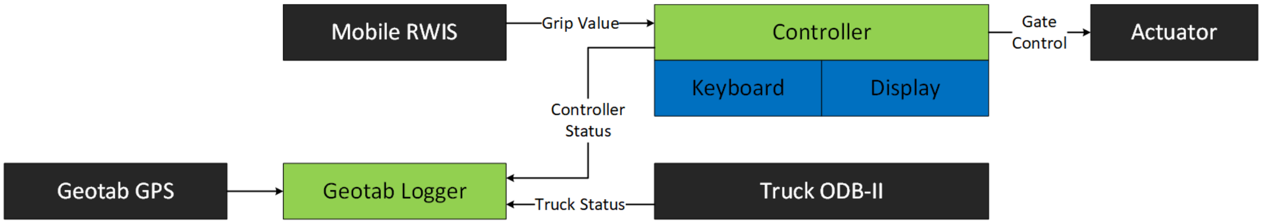


Figure 2-3: Sensor and data logging systems on the MassDOT truck

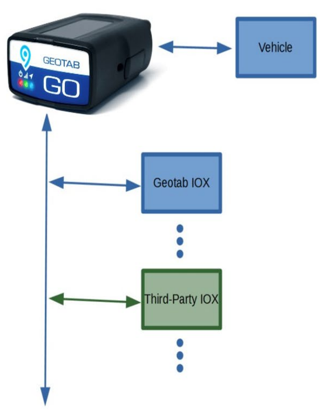
- The MD30 sensor (*34*) was designed for snowplows and other vehicles. It collects and transmits road surface state, grip, surface layer thickness, surface temperature, air temperature, dew point, frost point, and relative humidity. The unit is easily mounted on a plow vehicle behind the front metal bumper, as shown in Figure 2-4. The MD30 is designed to withstand heavy vehicle vibration and prevent water ingress. It attaches to the front of a snowplow or other vehicle. Bluetooth connection is used to transmit sensor data to a mobile application located on a device in the vehicle. The MD30 helps operators understand road conditions that can be used to deploy deicing techniques.

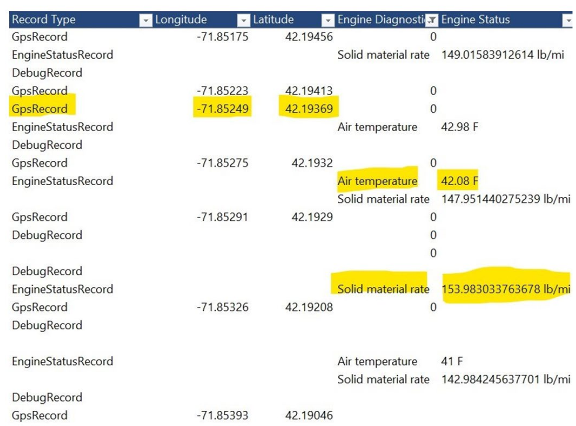
Figure 2-4: Current MD30 sensor installed on the MassDOT truck

- SpreadSmartRx is designed to control the spreading of granular or liquid material using feedback sensors, "Closed Loop operation," or "Open Loop operation." Feedback sensors allow the SpreadSmartRx to measure outputs and make real-time adjustments for more consistent control. The box has a variety of knobs to control the spreader. The box can adjust specific materials' material type, calibration, and spinner speed. It records readings of spreader output for each uniquely named material. It also stores calibration values of spreader hardware, system setup, and operating parameters. These recorded data can be uploaded or downloaded using a laptop PC serial port. Figure 2-5 shows the SpreadSmartRx box connections. The unit has a liquid crystal display (LCD) and keyboard (for control knobs) to assist control.

Figure 2-5: SpreadSmartRx control unit for controlling salt rate

- Geotab, as shown in Figure 2-6, is a telematics device connected to the vehicle's onboard diagnostics port. The SpreadSmartRx enables the collection of SpreadSmartRx data, specifically the salt rate, by the Geotab software using a custom protocol (IOX). The Geotab logger is used to extract the road treatment salt rate. The resulting data from the Geotab logger is available in comma-separated values (CSV) file format. The Geotab report highlighted in Figure 3-11 (shown later) provides logged salt rates and corresponding GPS coordinates. Geotab logs air temperature, road temperature, and the rate at which deicing material (solid or liquid) is applied. Effectively, it records the SpreadSmartRx control unit's data. However, Geotab does not capture data from the MD30 sensor, hence the need for a separate logging mechanism. The Geotab platform also collects vehicle information such as location, speed, fuel consumption, engine diagnostics, GPS info, and more. The data is transmitted to Geotab software, which is processed and analyzed to provide actionable insights to fleet managers.





Record Type	Longitude	Latitude	Engine Diagnosti	Engine Status
GpsRecord	-71.85175	42.19456	0	
EngineStatusRecord			Solid material rate	149.01583912614 lb/mi
DebugRecord				
GpsRecord	-71.85223	42.19413	0	
GpsRecord	-71.85249	42.19369	0	
EngineStatusRecord			Air temperature	42.98 F
DebugRecord				
GpsRecord	-71.85275	42.1932	0	
EngineStatusRecord			Air temperature	42.08 F
			Solid material rate	147.951440275239 lb/mi
GpsRecord	-71.85291	42.1929	0	
DebugRecord			0	
			0	
DebugRecord				
EngineStatusRecord			Solid material rate	153.983033763678 lb/mi
GpsRecord	-71.85326	42.19208	0	
DebugRecord				
EngineStatusRecord			Air temperature	41 F
			Solid material rate	142.984245637701 lb/mi
DebugRecord				
GpsRecord	-71.85393	42.19046		

Figure 2-6: Geotab logger and the recorded sample data

2.3.2 New Hardware Integration

The objective of the new hardware is to integrate the local data logger (LDL) into the existing hardware on MassDOT's truck and independently record all the mobile RWIS information and the road condition information, with the flexibility of customizing the data acquisition configurations and without interfering with the existing hardware. By the time this project was completed, the Geotab logger only recorded the SpreadSmartRx and the truck engine information. Therefore, the MD30 sensor also relies on the LDL to record all the data. Figure 2-7 shows the schematic diagram of the LDL with respect to the existing hardware. In this diagram, the gray blocks (video camera, XSens GPS and Geotab GPS, mobile RWIS, truck ODB II, and actuator) represent all the available sensors instrumented in this study.

In contrast, the green blocks (two data loggers and a controller) represent the computation units used for integrating collected data and subsequently processing them. The two orange boxes represent the key algorithms/models (RSC and SRP) developed in this study, whereas the blue boxes represent the input devices (keyboard and display) that might require the operator's engagement. For hardware integration, the red bounding boxes in Figure 2-7 represent where the research team carried out data I/O and the power supply works concerning the overall system.

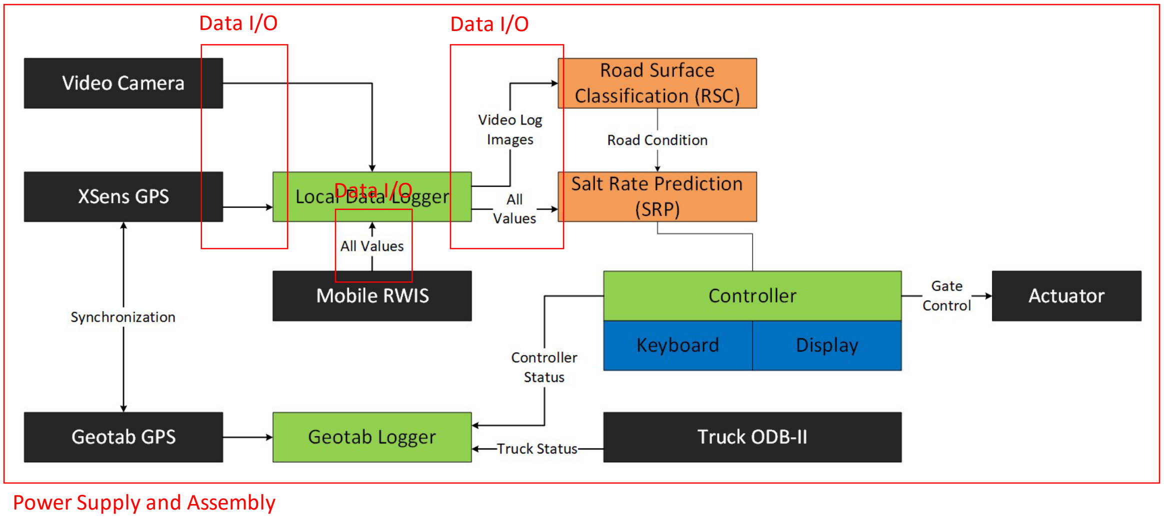


Figure 2-7: Hardware development for the new system

Figure 2-8 shows the detailed schematics of the Data I/O interfaces and the power supply interfaces for the newly integrated hardware. Details on the data connection and power specification can be referred to in Appendix 6.3.

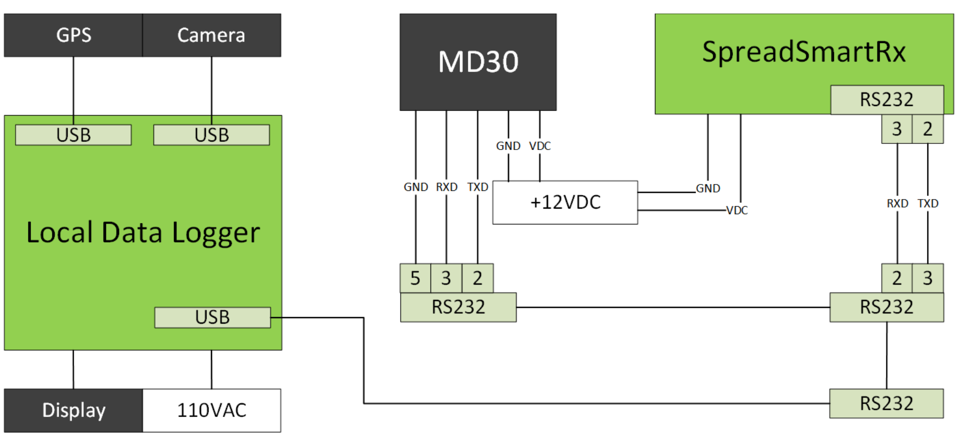


Figure 2-8: Data I/O and power supply schematics

Specifically, the GPS (i.e., Xsens MTi-G-710) and the video camera (i.e., Teledyne FLIR GS3-U3-51S5C-C) are directly connected with the LDL through the universal serial bus (USB) 3.0 ports, whereas the MD30 is connected with a Y-splitter for RS232 so that the feed to the SpreadSmartRx is not affected by the feed to the LDL. The feed from the MD30 is then connected with the LDL through a serial-to-USB interface. The data feed from the MD30 to the LDL was set up differently for the instrumentation using the UMass vehicle (for system development and testing purposes) and the MassDOT truck (for data collection and deployment purposes). For the UMass vehicle, the LDL works as the controller and actively requests the data from the MD30 by sending a data request command, whereas, for the MassDOT truck, the LDL works as a listener and only receives a copy of the MD30 data that is directly sent to the SpreadSmartRx controller, because the data request command is triggered by the SpreadSmartRx controller. The details of the hardware configuration for both the UMass vehicle and the MassDOT truck can be referred to Appendixes 6.2 and 6.3. Figure 2-9 shows the final configurations of the UMass vehicle and the MassDOT truck.

Figure 2-9: Hardware on the UMass vehicle (left) and the MassDOT truck (right)

2.4 Intelligent Salt Application System: Software

The objective of the software development is to ensure that the LDL can keep track of all the data feeds from the sensors and the Geotab data logger, as presented in Section 2.3. Figure 2-10 shows the software's basic functions corresponding to the sensors: logging and fusion. The first part of the software will control LDL itself to log the video camera, GPS, and MD30 data into a single spreadsheet that is synchronized through the LDL's time stamp, whereas the other part of the software will merge the LDL's logging data with the Geotab's logging data. As noted in Section 2.3, the Geotab logger, at the time of the project, could not log the MD30 data. Therefore, the key purpose of fusing the Geotab logger's data is to ensure that the SpreadSmartRx and the truck status data can be synchronized and integrated with the LDL's data. The research team was able to directly feed the SpreadSmartRx's status (including the salt rates) into the LDL. However, as the MassDOT truck has remained on active duty, the research team was instructed to minimize the interference with the truck. Because obtaining the direct feed from the SpreadSmartRx requires more complicated wiring, the research team decided to rely on the Geotab logger's data for the salt rates.

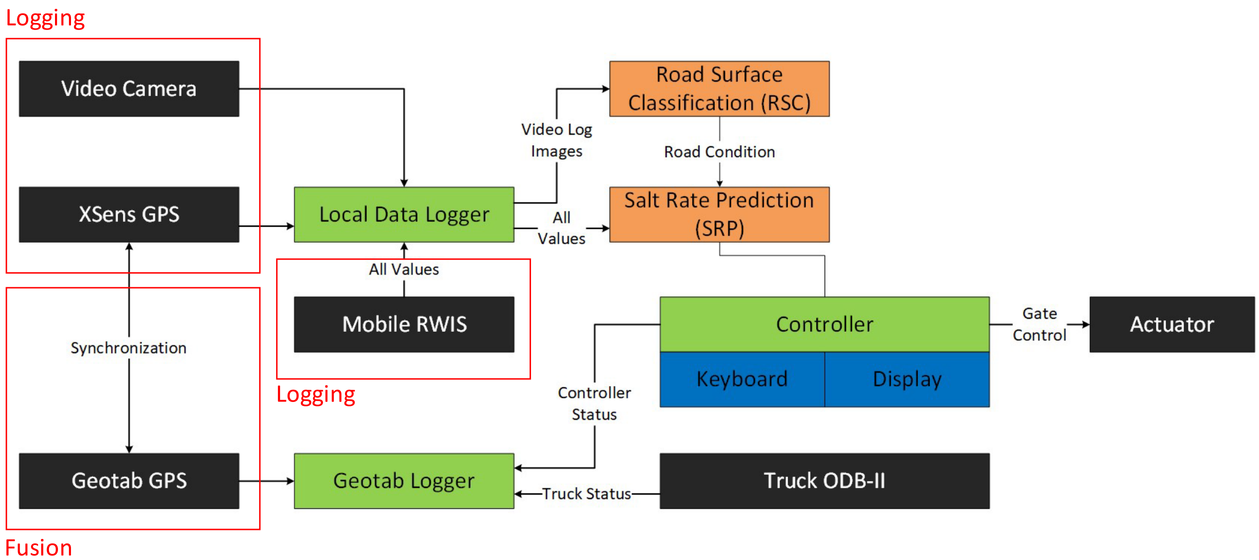


Figure 2-10: Software development for the new system

2.4.1 LDL Data Logging

The LDL data logging software aims to compile consolidated data logs from different sensors. As presented in Section 2.3, all the sensors are connected to the LDL through USB interfaces and will be independently dictated by the LDL. Therefore, a simple data logging software through multithread to dictate different ports will meet this objective. Therefore, the research team developed the data logging software using Python 3.10 and incorporated the MD30 interface client, FLIR SpinView, and Movella MT SDKs for the Vaisala MD30, the FLIR Grasshopper camera, and the Xsens GPS, respectively. The detailed configurations for different sensors can be referred to in Appendix 6.1. Figure 2-11 shows an example of the captured data, incorporation all the sensors' readings. As the sensors were capturing the data at different frequencies (i.e., 10 Hz, 200 Hz, and 5 Hz for MD30, GPS, and camera, respectively) 10 Hz was selected as the time interval as it dictates the complete information from MD30. In contrast, the GPS data were down-sampled by a scale of 20, and each image was captured for two MD30 data packages.

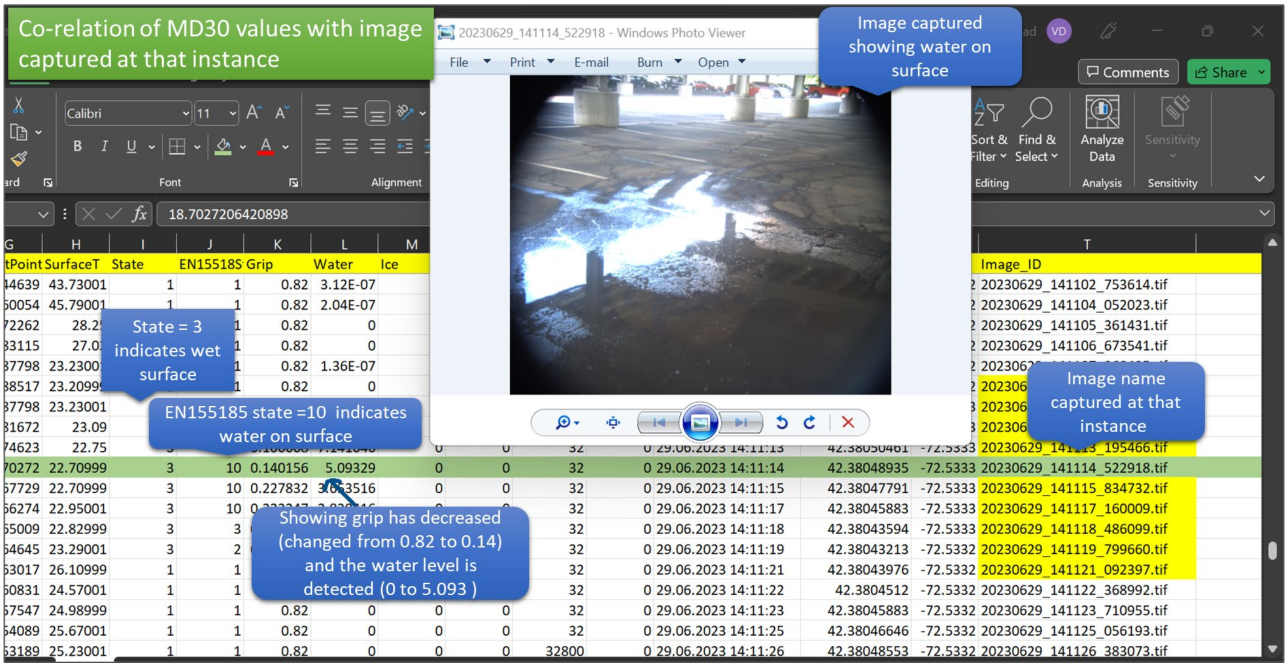


Figure 2-11: Sample data from the developed software

2.4.2 LDL and Geotab Data Fusion

The Geotab and MD30 loggers share synchronized time stamps, which can be leveraged to merge information into a single log. Road condition data collected before and after treatment is needed when evaluating road salt treatment effectiveness. Data logging with a two-hour difference could be used, although it would make time-stamp-based merging impractical. Therefore, data integration in these cases requires an additional common parameter, GPS coordinates. These coordinates are collected separately by the Geotab and MD30 loggers and used to merge logged information. A unified data log, the "Final CSV" block in Figure 3.4 (shown later in the report), incorporates information from the MD30 sensor, camera input, GPS coordinates, and the salt rate. This information can be used to execute a salt rate prediction model that makes decisions based on road-based data, as shown in Figure 2-12.

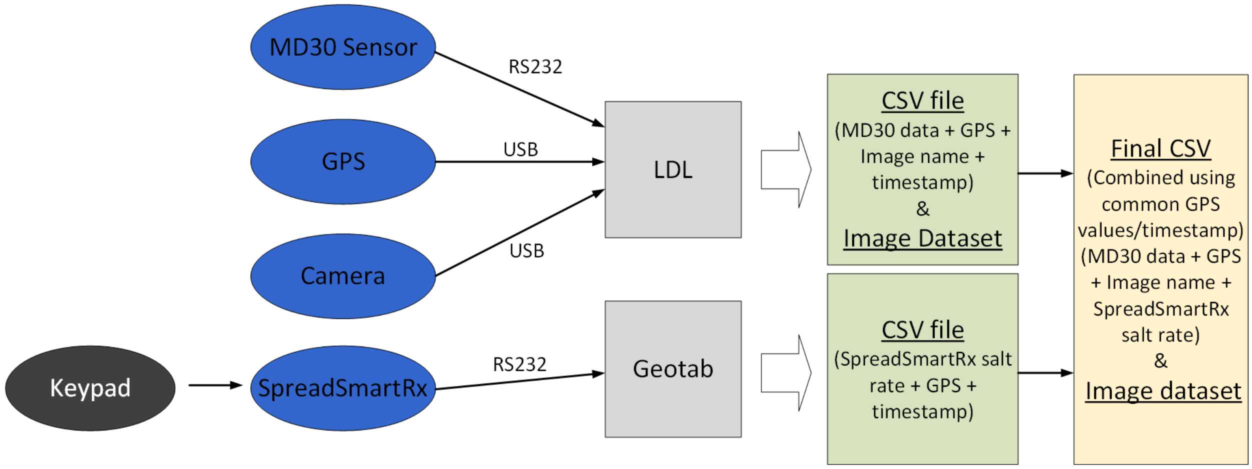


Figure 2-12: Data fusion schematic from the LDL and Geotab

GPS coordinates, latitude, and longitude values merge data from the local and Geotab loggers. The nearest coordinates from both data sets can be located using the Python GeoPy library (*35*) or the Haversine formula (*36*). BallTree or KDTree data structures can be used for spatial searches of the data set to find the nearest neighbors of a point.

Data is collected once per second for 30 to 40 minutes. The BallTree algorithm was selected due to its proficiency in managing large data sets where it is necessary to find the nearest neighbors of points in the data set. The Haversine formula calculates the shortest distance *d* between two points on the surface of a sphere, given latitude and longitude coordinates. It is expressed as:

$$a = \sin^2\left(\frac{\Delta\,\mathrm{lat}}{2}\right) + \cos(\mathrm{lat}_1)\cdot\cos(\mathrm{lat}_2)\cdot\sin^2\left(\frac{\Delta\,\mathrm{long}}{2}\right)$$
$$c = 2\cdot atan2\left(\sqrt{a},\sqrt{1-a}\right)$$
$$d = R\cdot c$$

Where:

- Δlat is the difference in latitude between the two points.
- Δlong is the difference in longitude between the two points.
- lat_1 and lat_2 are the latitudes of the two points, respectively.
- R is the radius of the Earth (mean radius ≈ 6,371 km).
- a is the square of half the chord length between the points.
- c is the angular distance in radians.
- d is the distance between the two points along the sphere's surface.

2.5 Intelligent Salt Application System: Algorithm

The algorithms aim to improve the system's road condition identification reliability by recognizing them from the images captured by the instrumented camera. The model should identify dry, wet, streaming water, snowy, slushy, and snow-covered wheel track surfaces to cover all the common road surface conditions. Namely, the algorithm is called the road surface condition algorithm or the RSC model.

The MD30 sensor reports road surface conditions through its sensor observation. However, an MD30 sensor has a narrow focus, which limits its surface condition assessment capabilities. For example, if the MD30 sensor is exposed to a small patch of a wet surface on a snow-covered road, as depicted in Figure 2-13, while the remainder of the surface is snowy, the road may be classified as wet rather than snowy. This discrepancy can result in inaccurate salt rate calculations, hampering efficiency. Hence, the RSC model is necessary. The model analyzes multiple road images and predicts overall surface conditions. By considering visual data beyond the scope of the MD30 sensor, this model can provide a more comprehensive understanding of road conditions, leading to a more effective salt rate calculation. The Road Surface Classification model's output is combined with MD30 data to generate a salt distribution rate value, as shown in Figure 2-2.

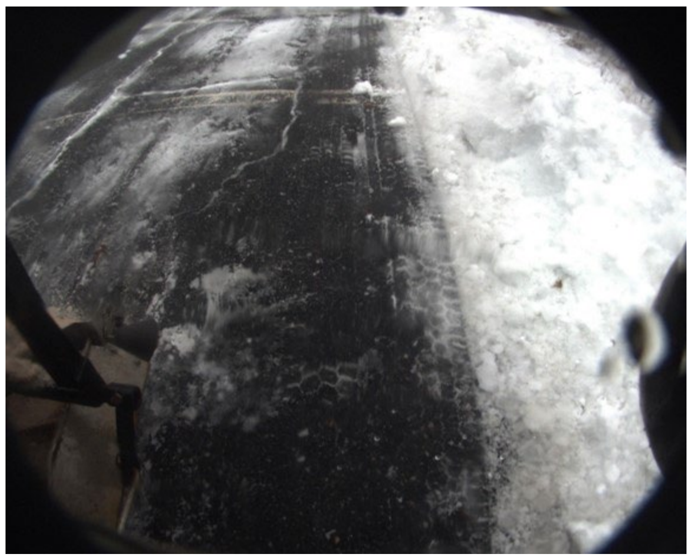


Figure 2-13: Road surface where snow accumulated inhomogeneously

2.5.1 Training Data Set Collection

To develop an RSC model capable of distinguishing surface conditions, obtaining a data set of thousands of images encompassing all relevant categories is necessary. The ideal time frame to acquire the appropriate image set for snowy, slippery, and slushy surfaces would be from November through February, as Massachusetts experiences snowfall during that period. The classification for pavement surfaces consists of six categories: dry, wet, streaming water, snowy, slushy, and snow-covered with wheel track surfaces. These categories are derived from reported MD30 road conditions parameters. Classifications are discussed further in Section 3.0.

2.5.2 Model Architecture for Classification Model

Pretrained models for classification can be used, or a new model can be created from scratch using artificial neural networks (ANN) or CNN layers. Pre-trained models offer good accuracy, making them suitable for road surface classification. DenseNet121 is a pre-trained CNN model that offers excellent performance in image classification tasks (*37*). This model can serve as a robust backbone for image classification tasks, allowing for adding layers and fine-tuning hyperparameters to improve accuracy. The DenseNet121 pre-trained CNN model was chosen as the basis for the RSC model. DenseNet121 achieves a top-1 accuracy of 75.0% and a top-5 accuracy of 92.3%, making it reliable for accurate image classification.

Additionally, the model is relatively lightweight, with a code size of 33 MB and requiring only 8.1 million parameters (*38*). For RSC, the top layer of the DenseNet121 model, designed for ImageNet class prediction, was removed. Instead, custom layers were added to the model to perform image classification into six road surface classes. The pre-trained "DenseNet121" is utilized as the base model for the RSC model, upon which additional classification layers were added. Training took place in the Google Colab environment, leveraging computing resources such as GPUs and TPUs to facilitate rapid training.

The model was trained on images with 64 × 64 pixels, each with three color channels (red, green, and blue [RGB]). DenseNet121 is a densely connected convolutional network with each layer connected. The DenseNet architecture is partitioned into multiple dense blocks. DenseNet121 includes four DenseBlocks with [6,12,24,6] convolutional layers. It also includes max pooling, transition, convolutional, and classification layers. The overall architecture is shown in Figure 2-14. A sequential model is used in the final RSC model, encapsulating the DenseNet model and additional layers. The newly added custom classification model includes a flatten, dense, and output layers. The flatten layer converts the 3D output tensor from the DenseNet121 into a 1D vector, input to the dense layers. Three dense layers are utilized to extract image features, and the output layer is configured with six units corresponding to the number of classes in the classification task. ReLU activation functions are employed for the dense layers, while "softmax" activation is utilized for the output layer.

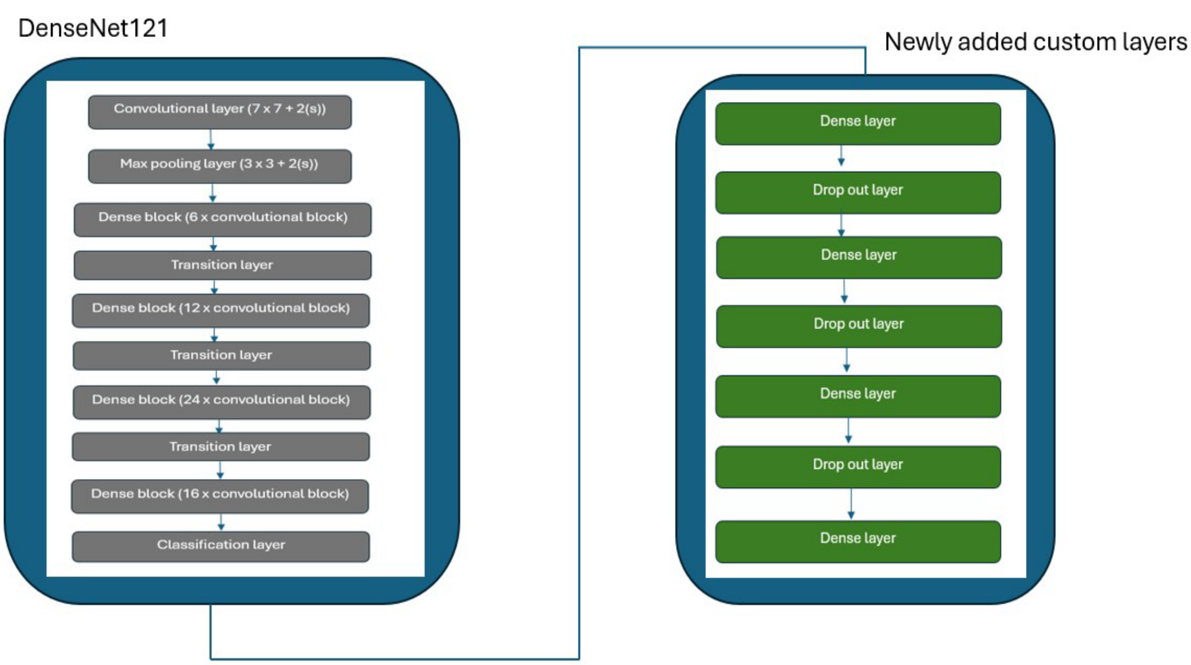


Figure 2-14: Architecture of the RSC model using DenseNet121

The classification model outputs a probability assigned to each class. The category or class of the image is determined by selecting the class with the highest probability. The final road surface category of the corresponding image will then be provided to the salt rate prediction model to decide the salt rate.

2.5.3 RSC Classification Definition and Classification

This step aims to define and classify the road surface conditions from the images that consistently represent the surface condition parameters reported by the MD30 sensor. To achieve this goal, a custom image data set was created using 10,000 images recorded in Amherst and Auburn, MA. The FLIR camera with a wide lens was used for this experiment. The setup shown in Figure 4.1 was used to collect the images on the UMass Amherst campus. Images were collected on a MassDOT truck during road treatment in real-time weather events.

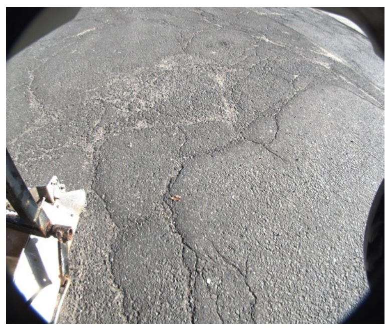
The data set comprises a total of 363 images for the Streaming Water category, 4,624 images for Dry, 1,316 images for Slushy, 439 images for Snow-covered with Wheel tracks, 2,886 images for Wet, and 373 images for Snowy. The categories match MD30 road state parameters. A custom data set was needed since differences in weather, roads, and individual understanding can affect data set categorization. Recorded images were manually categorized based on perceived road conditions DenseNet121 was employed to classify the road images. This algorithm inputs road images and generates probability scores for each surface condition class.

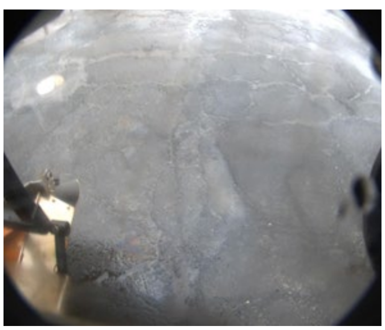
Figure 2-15: Camera configuration for RSC model training

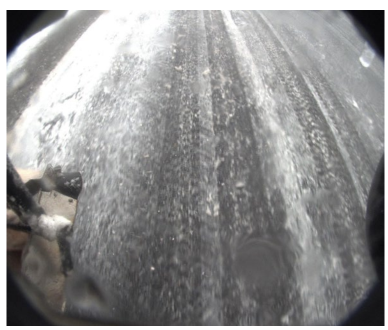
Table 2-2 shows that the RSC model's output categories are mapped to MD30 parameters. Notably, the new definition in the RSC model is similar to the MD30 definition, which merges some similar classes into a single cluster. In addition, the road condition Snow-covered with wheel tracks has been added as a new category. This surface condition has its salt rate recommendation (*39*), although the MD30 cannot distinguish it as a separate category. Sample road surface categorization images are shown in Figure 2-16.

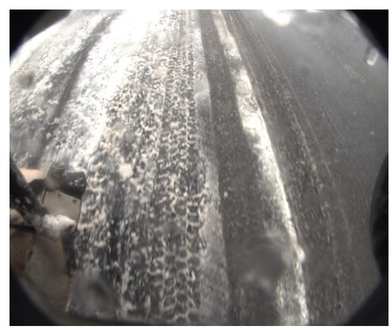
Table 2-2: Mapping of MD30 and RSC model classification

Road Surface Classification Model	**MD30 state parameter**		**MD30 EN1558 parameter**	
	Value	**Description**	**Value**	**Description**
Dry	1	Dry	1	Dry
Wet	2	Moist	2	Moist
	3	Wet	3	Wet
Snow	6	Snowy	11	Slippery
Snow-covered with wheel tracks	—	—	—	—
Slushy	7	Icy	11	Slippery
	9	Slushy	11	Slippery
Streaming water	—	—	10	Streaming water


Dry Surface


Wet Surface


Snowy Surface


Slushy Surface


Streaming Water Surface

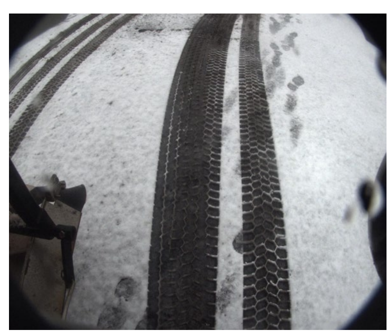

Snow-covered with Wheel Tracks

Figure 2-16: Sample road surface categorization images

2.6 Intelligent Salt Application System: Model

A comprehensive model that considers all road condition factors as input and generates corresponding salt rate values is needed to achieve accurate selections based on road-dependent conditions. Currently, MassDOT follows Vaisala salt rate guidelines (*40*) based on grip level. However, per Vaisala guidelines (*40*) and a Washington State University study (*41*), surface temperature and surface conditions also affect salt rate values. Thus, the decision-making model should consider grip levels, surface temperatures, and conditions to produce accurate salt rates. The salt rate prediction model can be represented as a flowchart in which the salt rate decision is determined by considering grip, surface temperature, road state, and the RSC model's output. Constructing the salt rate prediction model involves a series of conditions within the algorithm. Various combinations of grip levels and surface temperatures determine the primary root conditions. If any of these root conditions are satisfied, the algorithm assesses the surface condition using data from the MD30 sensor and the predicted surface state from the RSC model. Based on this evaluation, the final salt rate is determined. This section discusses the details of the developed salt rate prediction (SPR) model.

The latest (new) salt rates used by MassDOT to treat roads in the 2023–2024 winter are presented in Table 2-3. Previously used (old) values are included in the right column. Rates have been adjusted upward to increase deicing effectiveness. This salt rate model takes input from the MD30 sensor (surface and weather conditions) and the RSC model. The MD30 information includes grip, surface temperature, and road state indicated by "state" and "EN15518 state." Road grip level ranges from 0.10 (poor) to 0.82 (good).

Table 2-3: MassDOT salt rates for winter operation (based on MD30 grip reporting)

Grip level	New salt rates (lb/mi)	Old salt rates (lb/mi)
0.10–0.30	480	350
0.30–0.40	420	300
0.40–0.50	350	200
0.50–0.80	300	150
0.80–0.82	150	No salt

In the SRP model, the salt rate serves as the target variable. The rate depends on road surface parameters such as surface temperature and grip. The model was built using Vaisala guidelines (*40*) and information from Washington State University (*41*). The developed system makes decisions by combining MD30 sensor parameters such as surface temperature, grip, road surface state, and EN15518 road condition state. The salt rate prediction model was executed in real-time in a snowplow based on weather conditions, and model-generated values were provided to the salt distribution controller. To evaluate the performance of the new salt rate prediction model, the efficiency of the approach was compared with the efficiency of firmware auto mode operation based on grip measurements and manual salt rate control by the operator. The overall salt material used to treat roads and the overall grip improvement of the road were considered in assessments.

Figure 2-17 shows the updated decision model for salt rate. This model takes the existing decision model originally recommended by Vaisala (green) and integrates the outcome from the RSC model. (brown). The output of the final conditional block is the salt rate. The flowchart input comes from the MD30 sensor (road grip, surface temperature, and EN151518 state). Suppose the grip is within a range of 0.80 to 0.82, and the surface temperature is above 0°C. In that case, both the road state and EN151518 state indicate dry or moist conditions, or the RSC model output suggests a dry road surface; the conditions collectively confirm a dry surface. Under these circumstances, a salt rate of 100–150 pounds/miles, recommended by Washington State University (*41*), is deemed sufficient for road maintenance. If these conditions do not apply, checks in the flowchart are made for moderately low grip and surface temperature levels.

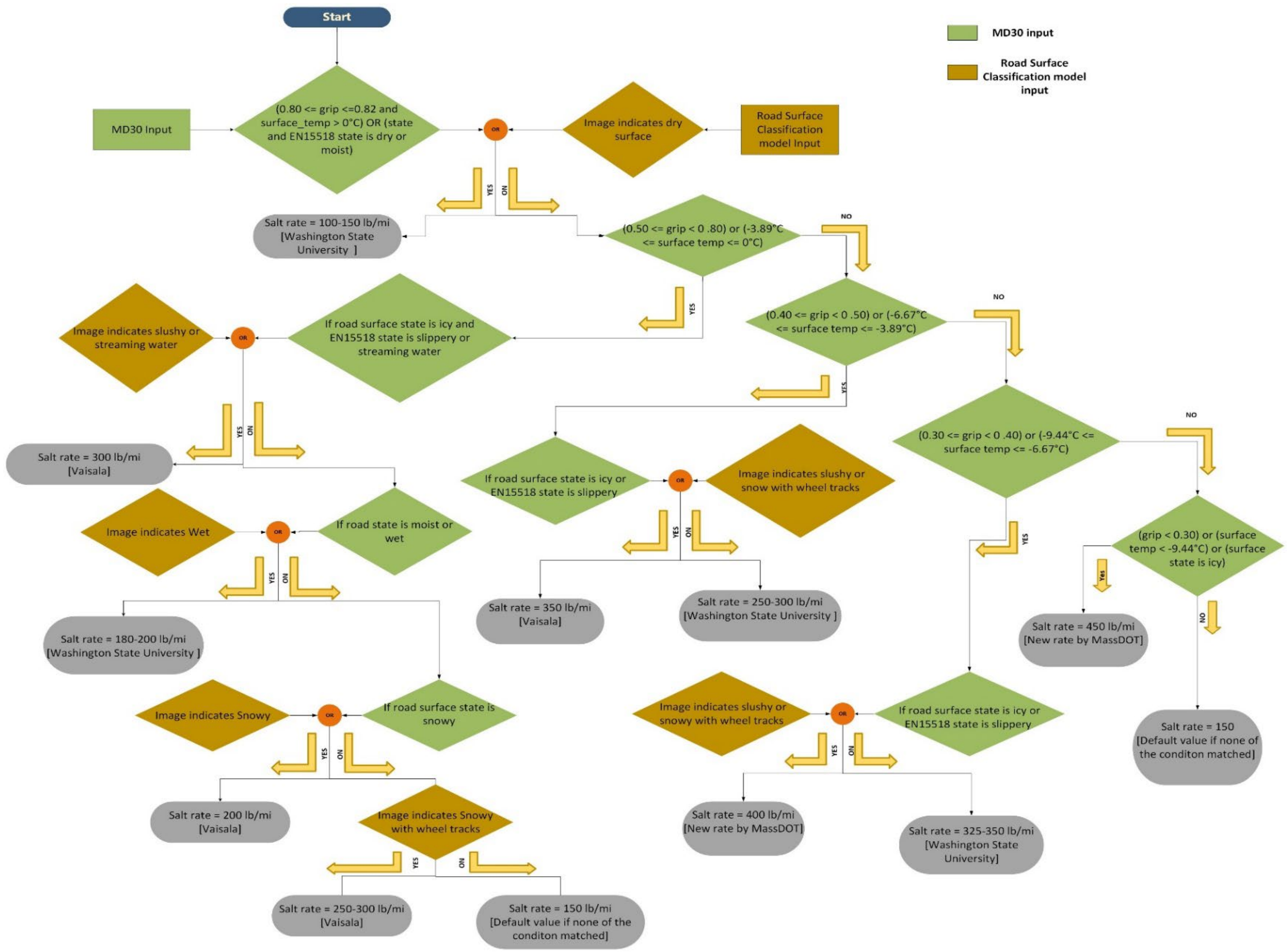


Figure 2-17: SRP model for surface treatment

The algorithm then checks the road's grip measurement to determine if it falls within the range of 0.50 to 0.80 or if the surface temperature is between −3.89°C and 0°C. Roads with a grip between 0.60 and 0.80 have moderate traction and, therefore, require less salt than surfaces with lower grip levels. Grip values within the range of 0.50 to 0.60 indicate slush or ice formation. Within the specified grip range of 0.50 to 0.80, surface conditions (wet, snowy, or slushy) must be considered, as different road conditions demand distinct salt application rates.

Once the condition (0.50 ≤ grip <0.80) or (−3.89 ≤ surface temp ≤ 0°C) is met, it is necessary to assess whether the road surface state is icy and the EN15518 state is slippery or streaming water or if the image shows slushy or streaming water. Under such conditions, a salt rate of 300 pounds per mile is considered, as recommended by Vaisala. If the road is not slippery, it must be determined whether it is wet or moist using the MD30 "state" parameter or the RSC model's image prediction output. A wet road condition requires a lower salt rate than a slippery surface, approximately 180–220 pounds per mile. If the wet condition is absent, snowy conditions are considered using the MD30 "state" parameter or the RSC model's indication of a snowy surface. If snowy conditions are confirmed, a salt rate of 200 pounds per mile is used. Finally, a check is made for the snow-covered with wheel track condition is made using the RSC model. A salt rate of 250–300 pounds per mile is used if this condition is confirmed. A default minimal salt rate of 150 pounds/mile is used if no conditions are satisfied.

If the condition (0.50 ≤ grip <0.80) or (−3.89°C ≤ surface temp ≤ 0°C) is not met, the algorithm proceeds to check for lower grip values and surface temperatures. A check is made to determine if the grip is in the range of 0.40 to 0.50 or if the surface temperature is between -6.67°C and -3.89°C. If this condition is satisfied, a check is made for slippery road conditions. If the state is snowy or EN15518 is slippery as per MD30 parameters, or the RSC model output for the image is snowy or snow with wheel tracks, a salt rate is 350 pounds per mile. If this condition is not satisfied, a salt rate of 250–300 pounds per mile is used.

If the condition (0.40 ≤ grip <0.60) or (−6.67°C ≤ surface temp ≤ −3.89°C) is not met, a check is made for lower grip level and surface temperature values. If the grip is in the range of 0.30 and 0.40 and the surface temperature is between −9.44°C and −6.67°C, information from the MD30 is needed, as shown in the flowchart. In this case, a salt rate of 400 pounds per mile is used if the MD30 road state is icy, the EN15518 state is slippery, or the RSC model indicates snowy or snow with wheel track conditions. A salt rate of 325–350 pounds/mile is used if the slippery road condition is not satisfied.

If the condition of (0.30 ≤ grip ≤ 0 .40) or (−9.44°C ≤ surface temp ≤ −6.67°C) is not satisfied, then a check is made for a grip level less than 0.30, a surface temperature less than −9.44°C or an icy surface state. If these conditions are satisfied, an aggressive salt rate of 450 pounds/mile is used. A default salt rate of 150 pounds/mile is used if these conditions do not hold. If the MD30 sensor output does not satisfy any of the conditions, the sensor output may be in error.

3.0 Results

This section presents the findings and analysis of salt treatment experiments conducted during winter events. The experiments assess the performance of the Road Surface Classification model. The initial two experiments, Experiment 1 (preliminary data logging testing with MD30, camera, and GPS) and Experiment 2 (establishing MD30 dual communication and preliminary data logging testing with MD30, SpreadSmartRx, camera, and GPS), aimed to validate hardware and software. Experiment 3 (RSC algorithm evaluation) involved image data collection and the development of a machine learning (ML) model to identify surface states, while Experiment 4 (SRP model validation) focused on data collection during salt treatment, execution of the salt rate prediction model, and performance evaluation alongside current MassDOT practices.

3.1 Validations of Hardware and Software (Experiments 1 and 2)

The outcome of Experiment 1 was the successful implementation of the LDL on the UMass vehicle, with synchronization between MD30 and camera data. In Experiment 2, all components and connections were successfully mounted on the MassDOT truck. Experiment 2 also established the MD30's communication with the LDL and the SpreadSmartRx. This setup enabled the generation and validation of the logger, which records MD30, camera, and GPS information on the LDL, and the Geotab logger, which records the salt rate and GPS data. Detailed information on logger validation methods, approaches to check synchronization between the camera and MD30, pinout information for MD30's dual communication with LDL and SpreadSmartRx, and final component placement and connections on the MassDOT truck are available in Appendix C.

3.2 Validation of the RSC Model (Experiment 3)

Experiment 3 evaluated a machine learning model capable of categorizing images into dry, wet, snowy, snow-covered with wheel tracks, streaming water, and slushy. During model training, the sample data set is randomly shuffled, and 80% of the data is used for training, while the remaining 20% is used for model testing. The training accuracy of the model, which refers to the accuracy of a machine learning model on the 20% training data set, is 86.7%. The model was evaluated using fivefold cross-validation, receiver operating characteristics, mean average precision, top-three accuracy, F1 score, and a precision–recall curve. These metrics are described subsequently in this section.

The data set is randomly divided into five groups (folds) in fivefold cross-validation. The model is trained on fourfold, while onefold is reserved for model testing. This process is repeated five times, with each fold used once as the test set. Therefore, a different fold is the test set in each iteration, while the remaining folds are used for model training. For this evaluation technique, the accuracy values obtained were 88.9%, 91.4%, 90.1%, 88.8%, and 88.5%. The overall mean accuracy of fivefold cross-validation is 89.5%, with a standard deviation of 1.1%. The fivefold cross-validation score indicates a 1.1% variation in performance across different data subsets. This variation is tolerable, and the model is expected to perform well on unseen data.

A receiver operating characteristics (ROC) curve is a graphical representation of a model's performance. The curve is a graph of true positive rate versus false positive rate. A true positive rate signifies the proportion of positive instances the model identifies as positive. A false positive rate signifies the proportion of negative instances the model incorrectly classifies as positive. The most common way to analyze a ROC curve is with an area under curve (AUC) value. AUC ranges from 0 to 1, where a higher value indicates better overall performance. Figure 3-1 shows that the AUC for dry surface classification is the highest, suggesting strong discrimination capability for dry road conditions. For all other road classifications—slushy, snow-covered with wheel tracks, snowy, streaming water, and wet—the AUC values are also high, indicating that the model performs well in discriminating between these road surface conditions.

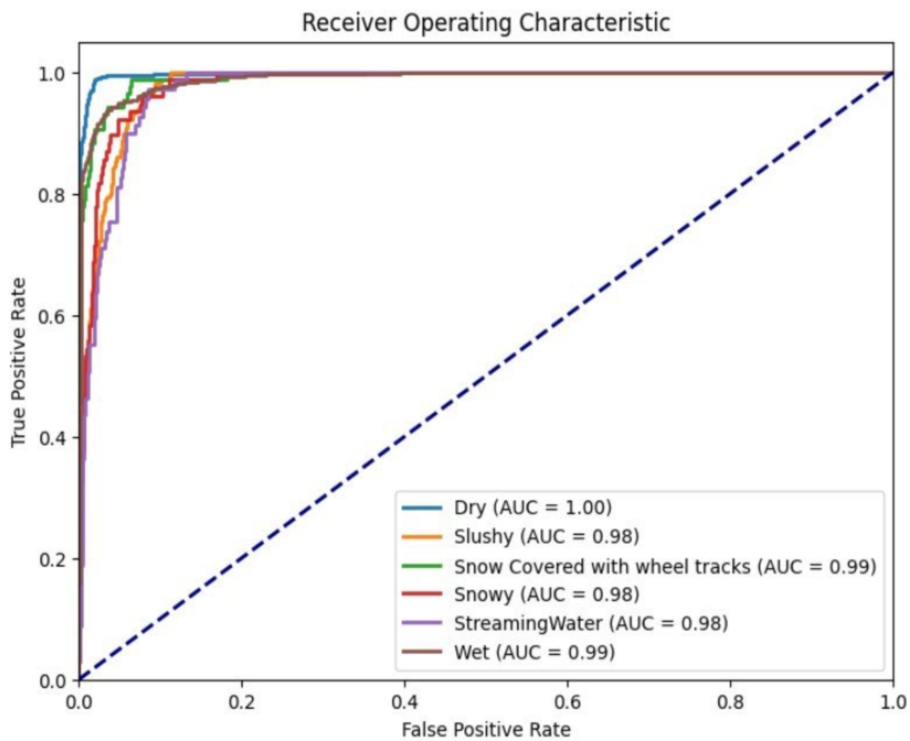


Figure 3-1: ROC curve

In model evaluation, precision is the proportion of true positive predictions out of all positive predictions made by the model. At the same time, recall is the proportion of true positive predictions from all positive instances in the data set. The precision–recall curve plots precision and recall at different classification thresholds. A high AUC represents both high recall and high precision. A precision–recall curve for the RSC model is shown in Figure 3-2. Dry, snow-covered wheel tracks and wet surfaces have AUC values greater than 0.90, indicating that the RSC model's predictions for these classes are highly reliable, and the model can identify most of the actual instances of each class, indicating high precision and recall value. The slushy and snowy classes have AUC ranges from 0.80 to 0.90, suggesting that the model balances precision and recall. Still, it might either miss some true instances (lower recall) or include some incorrect ones (lower precision). However, the streaming water classification has a poor AUC value of 0.54, indicating that the model is unreliable for detecting streaming water and could lead to many missed detections and false predictions. There is room for improvement for this class, particularly a need to acquire a better data set that can identify and incorporate additional relevant features to capture the class's characteristics better.

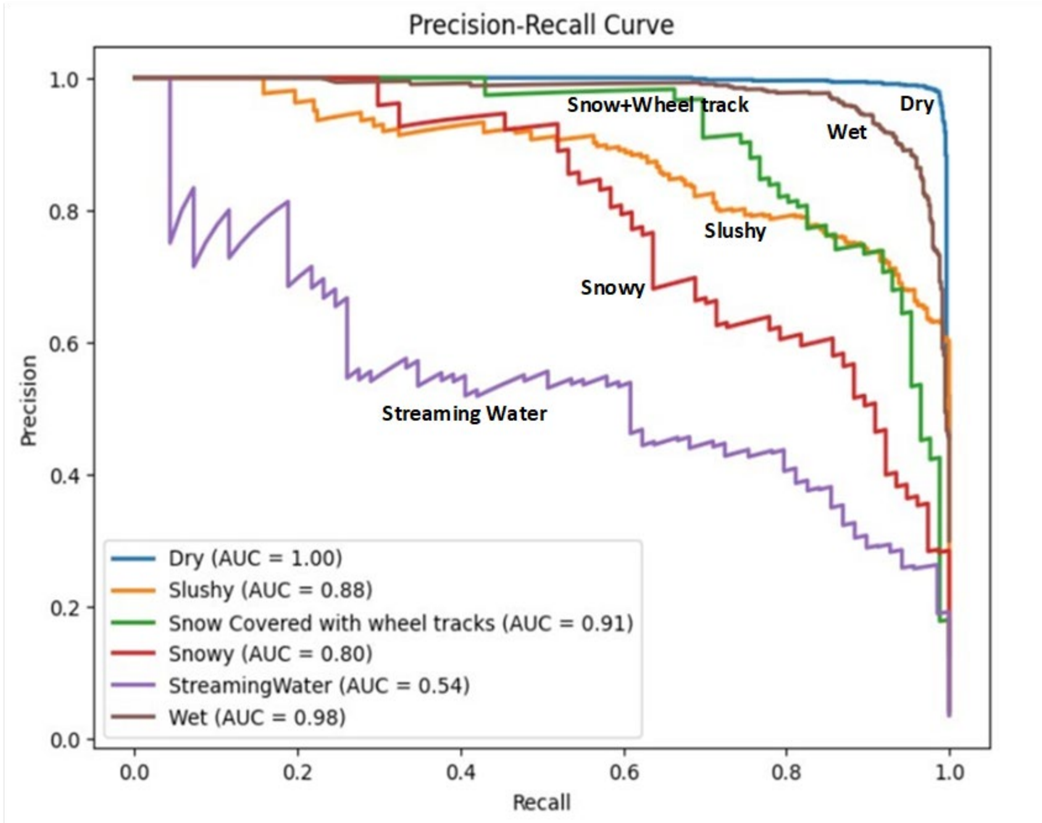


Figure 3-2: Precision–recall curve

Average precision (AP) is a metric used to summarize a specific class's precision–recall curve (PR curve). It is recorded by the model across all recall levels and is calculated as the area under the PR curve. The AP values for each class are as follows: 99% for dry surface, 88% for slushy surface, 91% for snow-covered with wheel tracks surface, 80% for snowy surface, 54% for streaming water surface, and 98% for wet surface. Hence, the model is highly effective at identifying dry and wet surfaces, detecting slushy and snow-covered wheel track surfaces, and detecting snowy surfaces. However, it is not reliable for classifying streaming water surfaces. The mean average precision (mAP) is the mean of the AP values calculated across all classes in the data set. It provides an overall performance measure for the model across multiple classes. The mAP of the RSC model is 85.3%, which indicates that, on average, the classification model has a good level of precision across all classes and is sufficient for a road classification requirement.

Top-n accuracy is a performance metric used in multiclass classification tasks, where a prediction is considered correct if the true class label is among the top n predicted classes with the highest confidence scores. In the case of the RSC model's performance evaluation, the top three accuracies have been calculated. This metric assesses the model's ability to predict the correct class when considering the top three predicted classes out of a total of six classes. Achieving high accuracy within the top three predictions demonstrates promising model performance. Notably, the RSC model has achieved an impressive top-three accuracy of 99.45%.

F1 score is a popular metric used in classification models. It is the harmonic means of precision and recall. F1 combines these two metrics into a single value, providing a balanced measure of a classifier's performance. The F1 score ranges from 0 to 1, with a score closer to 1 indicating better performance. For the RSC model, an F1 score of 0.90 indicates a strong balance between precision and recall in a classification model. It reflects an RSC model that is both precise and robust in identifying the true instances of a particular class, with a very good trade-off between not missing true instances and not misclassifying other instances as the class of interest. This score is suitable for the project application.

While the model has demonstrated promising performance across various evaluation metrics, it is important to note that it has been trained and tested on a relatively small data set of 10,000 images. This data set does not comprehensively cover all classifications in detail, making the model unsuitable for real-time testing scenarios at this stage.

3.3 Validation of the SRP Model (Experiment 4)

Experiment 4 evaluates the performance of salt treatment practices and the salt rate model. Salt treatment effectiveness is evaluated using two key metrics: overall improvement in road grip and the total amount of salt utilized during treatment. Two databases are required to assess these factors. The first database includes MD30 sensor data capturing road conditions, camera images, GPS coordinates, and corresponding salt application rates used for treatment. This data set, obtained using the loggers evaluated in Experiment 2, provides insights into grip levels and salt usage during road treatment. The second database, collected approximately 1 to 2 hours after treatment along the same route, includes MD30 parameter values that capture road conditions and camera images annotated with GPS coordinates. This post-treatment data set offers valuable information regarding road condition improvement, particularly grip enhancement.

This experiment collected data in three different spread controller modes, including auto-grip mode, manual mode, and the proposed mode using SRP. The salt spreader system has two modes: manual and automatic. In heavy snow storms, the operator manually runs the salt spreader system, deciding salt rates based on his understanding of the weather and road conditions by visual analysis. The operator uses a salt spreader in auto-grip mode if it is a moderate snowstorm based on Table 2-3.

3.3.1 Auto-Grip Mode Salt Treatment

Data was first collected when the controller was set to auto-grip mode. Logs were generated before and after treatment using GPS coordinates and the spatial merging technique discussed in Section 3.3.2. The before and after salt treatment grip values over the treatment distance were plotted, as depicted in Figure 3-3. Grip values range between 0.10 (poor) and 0.82 (good).

In Figure 3-3, the distance traveled by the truck is plotted on the x-axis in miles, and grip values are plotted on the y-axis. The blue line represents grip values before the salt treatment trip, while the red line represents grip values after the salt treatment. Dotted blue (lower) and dotted red (upper) lines indicate the overall mean values before and after salt treatment. The grip line after treatment indicates that, in most of the trip, the grip has improved compared to before treatment of the road. Additionally, the overall mean of the grip values throughout the distance traveled has increased by 0.03 compared to before treatment, as indicated by the dotted blue and red lines representing the mean value of the grip data collected before and after treatment. In this evaluation mode, it is important to consider

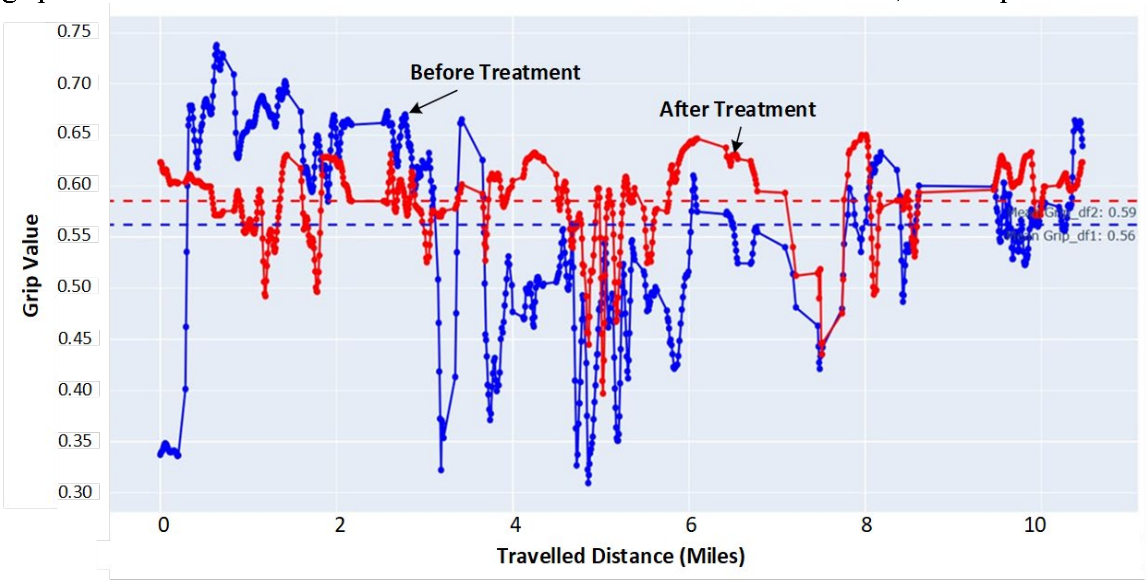


Figure 3-3: Grip values before and after treatment for the auto-grip mode

weather conditions. The weather was moderately snowy when the data set was collected before salt treatment, with surface temperatures ranging between −0.33°C to 4.41°C. Two hours later, when data was collected after salt treatment, the weather was cloudy, and there was no snowfall, with surface temperatures ranging between 1.97°C and 14.09°C. Rising surface temperature helps melt the snow faster. So, in the after-treatment analysis of auto-grip mode, variation in surface temperature also plays a significant role.

3.3.2 Manual Mode Salt Treatment

The second data set was collected while the operator manually operated the spreader controller based on their road conditions assessment. A video of the controller's operation during the trip was recorded to capture salt rate information during manual mode. This video documented the operator's adjustments to the salt rate. The corresponding salt rate for each time stamp was manually entered into the logger using the video as a reference. The salt rate was originally displayed as a percentage but was subsequently converted to pounds per mile. This conversion was achieved by calculating the percentage of the maximum salt rate allowed for the controller per mile, which was set at 1,200 pounds. For instance, if the operator set the controller to 26%, that percentage of the maximum allowed salt rate per mile (1,200 pounds) was calculated, and this value was then manually entered into the Geotab logger for the corresponding time stamp. The MD30 logger was used to analyze road conditions, and the Geotab logger was used to determine the total salt rate of the material used in manual mode road treatment.

To assess the effectiveness of the manual mode road treatment, a trip was conducted along the same route one hour after the initial treatment. During this trip, the collected MD30 data and GPS coordinates were utilized to evaluate the overall road grip. The MD30 data logs collected before and after manual mode salt treatment were merged using spatial analysis with the help of GPS coordinates collected by the loggers. Synchronization techniques were used to combine the data sets. Road grip was evaluated by plotting before and after salt treatment grip values against the distance traveled by the truck.

In Figure 3-4, the *x*-axis represents the distance traveled on the road, while the *y*-axis represents grip values. The blue line represents grip values collected before manual mode salt treatment, while the red line represents grip values collected after manual mode salt treatment. Although the red line has not shifted noticeably upward compared to the blue line, it closely follows the same trajectory. This suggests that the grip values observed before manual salt treatment have not significantly improved; the overall grip level has been maintained with the applied salt rate. However, these grip levels seem acceptable considering the weather conditions before and after manual salt treatment.

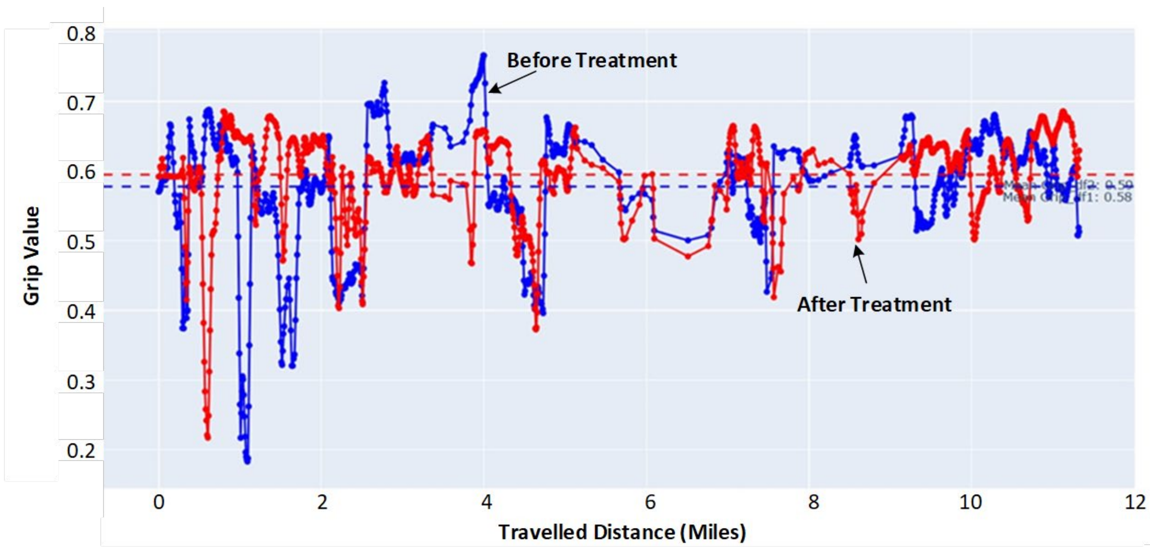


Figure 3-4: Grip values before and after treatment for the manual mode

Before treatment, there was heavy sleet rain with a surface temperature ranging from −3.79°C to 2.65°C, while during the evaluation of manual salt treatment performance, there was sleet mixed with snow with a surface temperature ranging between −1.79°C to 6.07°C. Hence, the observed grip levels are deemed satisfactory, given the challenging weather conditions. The means of the grip values before and after treatment are drawn with dotted red (upper) and blue (lower) lines, respectively. The plots show that the overall mean value of the grip improved by 0.01.

3.3.3 Proposed Mode Using SRP Model

Salt treatment was performed per the salt rate prediction model, which takes input from the MD30 sensor for different road conditions and outputs the appropriate salt rate. This rate was then manually entered into the SpreadSmartRx controller using a keyboard. Grip values collected before and after treatment were plotted against the distance traveled by truck, as shown in Figure 3-5. The blue line represents the grip values recorded before treating the roads, while the red line indicates the grip values recorded after the salt treatment. This figure shows that the grip values for the first three miles after treatment are significantly shifted compared to the before-treatment values. Subsequent grip lines either closely follow each other or exhibit slight variations.

Overall, there is an improvement in grip values throughout the journey, as evidenced by the mean grip lines depicted in the graph. The lines show an overall improvement of 0.03 in the mean grip. The weather conditions were sleet mixed snow before salt treatment and snow during after-treatment data collection.

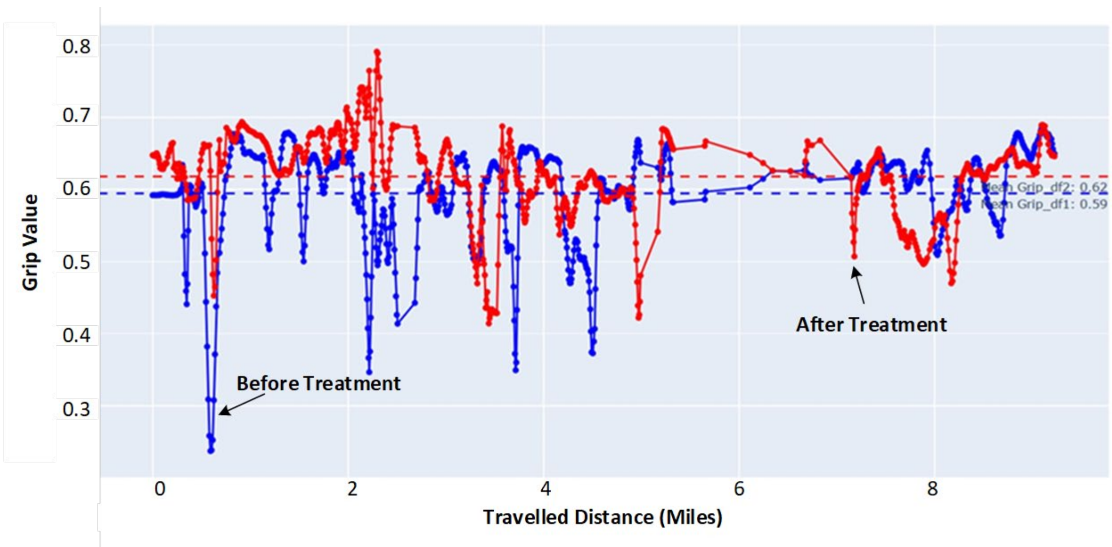


Figure 3-5: Grip values before and after treatment using the proposed mode

3.3.4 Salt Application Amount Comparison

Salt treatment was also evaluated by analyzing the total amount used in each treatment mode. For auto-grip mode, manual mode, and salt rate model modes, the Geotab logger recorded salt rates and corresponding GPS coordinates. Salt rates were measured in pounds per mile. The distances traveled between consecutive GPS points were logged to calculate the cumulative roadway salt spread. This distance was computed in miles using the geodesic distance function provided by the Geopy library. The amount of salt spread for each segment was calculated by multiplying the distance traveled in each segment by the corresponding solid material rate, as the salt rate is measured in pounds per mile. The total amount of salt spread was determined by taking the cumulative sum of salt spread across all segments.

Figure 3-6 shows cumulative salt spread during auto-grip, manual, and salt rate model modes. The distance traveled by truck in miles is shown on the x-axis, and the total salt spread on the roads in pounds is shown on the y-axis. Blue, red, and green lines show cumulative salt spread determined by the SpreadSmartRx controller for the auto-grip, manual, and proposed modes, respectively. The truck traveled 11.82 miles in auto-grip mode, and the total salt spread on the road was 3,590 pounds. In manual mode, the distance driven by truck was 13.53 miles, and the cumulative salt spread was 3,752 pounds. In salt rate model mode, the truck traveled 11.18 miles, and the total salt spread on the road was 2,369 pounds.

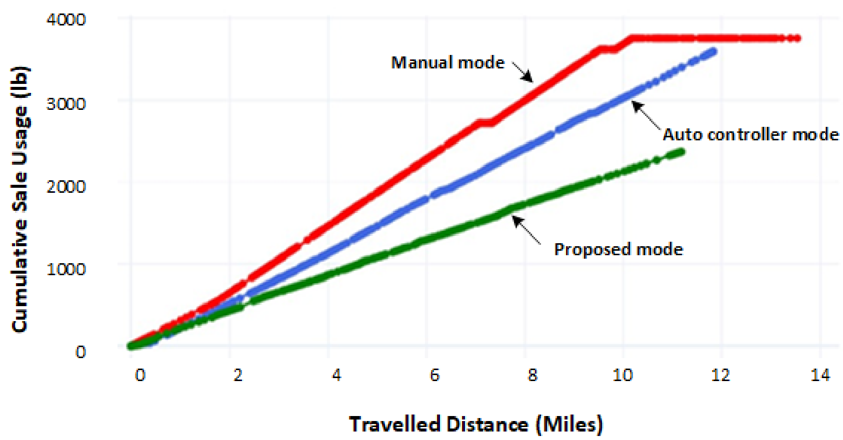


Figure 3-6: Cumulative salt on roads during auto-grip, manual, and proposed modes

The total amounts of salt used for road treatment and the distances traveled by truck in the auto-grip (upper) and salt rate model (lower) modes were verified using Geotab reports shown in Figure 3-7, in which the amount of solid (salt) material in the truck was checked at the start and end of each trip for each respective treatment mode. The total salt spread on the roads was determined by subtracting the initial amount from the final amount. Similarly, from the Geotab record, the truck solid spread distance values at the beginning and end of each log were used to calculate the total distance traveled by the truck during road treatment.

Device	Device Group	First Name	Date	Log Time	Record Type	Engine Diagnostic	Controller	Engine Status
Auburn STL942	Vehicle, Diesel, UMass Study		Jan 28, 2024	11:10:41 AM	EngineStatusRecord	Truck solid material total		1.5220824 US TON
Auburn STL942	Vehicle, Diesel, UMass Study		Jan 28, 2024	11:11:26 AM	EngineStatusRecord	Truck solid spread distance		9.69960131 mi
Auburn STL942	Vehicle, Diesel, UMass Study		Jan 28, 2024	11:47:00 AM	EngineStatusRecord	Truck solid spread distance		20.90292044 mi
Auburn STL942	Vehicle, Diesel, UMass Study		Jan 28, 2024	11:47:11 AM	EngineStatusRecord	Truck solid material total		3.32804 US TON
Auburn STL942	Vehicle, Diesel, UMass Study		Jan 28, 2024	11:47:22 AM	EngineStatusRecord	Truck solid material total		3.3355336 US TON
Auburn STL942	Vehicle, Diesel, UMass Study		Jan 28, 2024	11:47:33 AM	EngineStatusRecord	Truck solid material total		3.3360846 US TON

Device	Device Group	First Name	Date	Log Time	Record Type	Engine Diagnostic	Controller	Engine Status
Auburn STL942	Vehicle, Diesel, UMass Study		Jan 28, 2024	8:37:51 PM	EngineStatusRecord	Truck solid material total		0.0009918 US TON
Auburn STL942	Vehicle, Diesel, UMass Study		Jan 28, 2024	8:38:02 PM	EngineStatusRecord	Truck solid material total		0.0045182 US TON
Auburn STL942	Vehicle, Diesel, UMass Study		Jan 28, 2024	8:38:13 PM	EngineStatusRecord	Truck solid material total		0.0094772 US TON
Auburn STL942	Vehicle, Diesel, UMass Study		Jan 28, 2024	8:38:13 PM	EngineStatusRecord	Truck solid spread distance		0.09941936 mi
Auburn STL942	Vehicle, Diesel, UMass Study		Jan 28, 2024	9:09:46 PM	EngineStatusRecord	Truck solid spread distance		10.9982667 mi
Auburn STL942	Vehicle, Diesel, UMass Study		Jan 28, 2024	9:09:56 PM	EngineStatusRecord	Truck solid material total		1.1836582 US TON
Auburn STL942	Vehicle, Diesel, UMass Study		Jan 28, 2024	9:10:07 PM	EngineStatusRecord	Truck solid material total		1.1861928 US TON

Figure 3-7: Total distance traveled and salt used in auto-grip and proposed modes

3.3.5 Simulated Salt Treatment Modes

Data collected for auto-grip and salt rate model modes can be used in real-time and for simulations. Specifically, weather conditions and time differences between consecutive road treatments can be simulated, and expected salt rates can be determined. This approach allows for the comparison of salt treatments under the same environmental conditions.

A simulation was conducted to determine respective model outputs under the same weather conditions and application distances to ensure a fair comparison of salt usage between auto-grip and salt rate model modes. Environmental and GPS data logged while treating roads in auto-grip mode were used as input to the salt rate prediction model. The salt rate output suggested by the model was then recorded. In Figure 3-8, a solid blue line depicts the total salt used in auto-grip mode. A dashed blue line represents the simulated outcome of the total salt that would have been used in the proposed mode with the SPR model executed within the same environment. The total salt used in auto-grip mode is 3,590 pounds, whereas the total salt usage in the SPR model would have been 2,898 pounds.

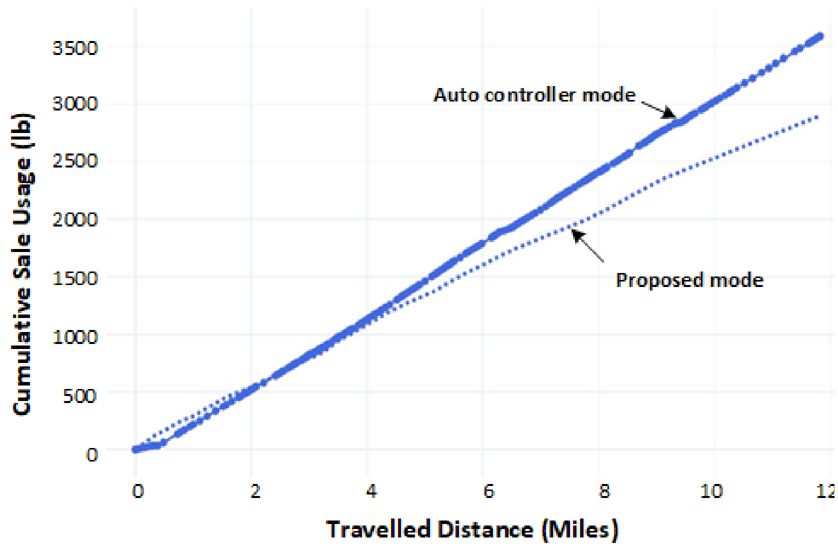


Figure 3-8: Total salt used in simulated proposed mode

In a similar experiment, environmental and GPS data collected during salt rate model mode was used to help determine expected outputs during auto-grip mode. The data is inputted into auto-grip mode, and output salt rates and total salt values are determined. In Figure 3-9, the solid green line indicates the amount of salt used in the proposed mode with the SPR model, while a dotted blue line indicates the salt that would have been used by the auto-grip mode in the same environment. The salt used by the proposed mode is 2,369 pounds, whereas the total salt that the auto-grip mode would have used was 3,454 pounds.

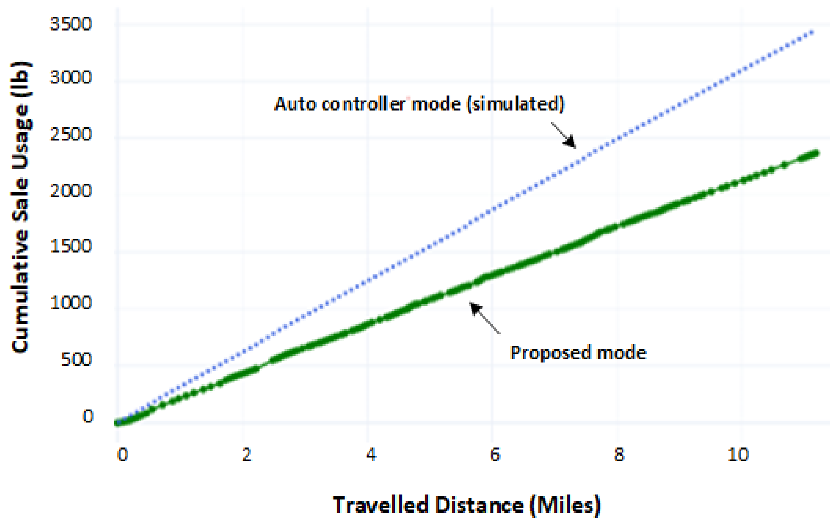


Figure 3-9: Total salt used in simulated auto-grip mode

Last, the SRP model relies on two input sources: the MD30 sensor data and the RSC model output. Since the RSC model could not be trained on a comprehensive data set covering a large range of road conditions, it was not employed for real-time salt rate decision-making for the experimentation in this study. Instead, the salt rate was solely determined by inputs from the MD30. Nevertheless, the environmental data collected in auto-grip mode and surface images can still be leveraged as input for the flowchart in Figure 2-17. The algorithm that implements the flowchart generates salt rate predictions utilizing input from both the MD30 sensor and the RSC model. This simulation uses logged environmental and GPS data collected in auto-grip mode during salt treatment.

In Figure 3-10, the total salt amount is calculated for the salt rate model mode under the same environmental conditions as auto-grip mode. The solid blue line represents the cumulative salt used in auto-grip mode. The dotted blue line indicates the total salt that would have been used by the salt rate prediction model with only MD30 input, while the dotted green line shows the total salt that would have been used by the salt rate prediction model with both MD30 data and the RSC model output as input. In auto-grip mode, 3,590 pounds of salt were used, whereas in the salt rate model with only MD30 input, the total salt usage was calculated to be 2,898 pounds. If the salt rate model had utilized both MD30 and RSC model input, the cumulative salt total would have been 2,949 pounds.

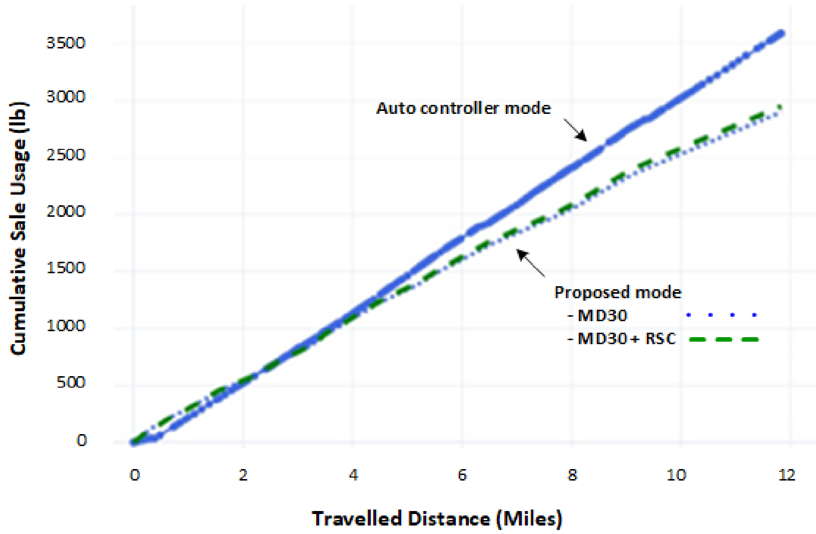


Figure 3-10: Total salt used in simulated proposed mode with RSC model input

3.3.6 Comparative Analysis of Salt Treatment Methods

This section presents a comparative analysis and discussion of the findings from experiments conducted to evaluate the performance of the salt rate prediction model in both real-time and simulated scenarios. It shows how the salt rate prediction model surpasses current practices and notes the advantages of the salt rate prediction model over existing methods.

After auto-grip mode salt treatment, grip improved from 0.56 to 0.59, and the total salt used was 3,590 pounds. Before the salt treatment, there was moderate to heavy snowfall, but the snow had completely stopped after the treatment. Additionally, the mean surface temperature increased from 2.02°C to 3.94°C. So, in this evaluation, along with salt treatment, environmental conditions helped to improve the road's grip. If the salt rate model had been used for road treatment under the same weather conditions, the resulting salt usage would have been 2,898 pounds, a savings of 692 pounds. If the salt rate model had been utilized with RSC input in the same weather conditions, the total salt usage would have been 2,949 pounds. Including the RSC input leads to a 51-pound difference in salt usage versus the salt rate model without it.

It remains a challenge to ascertain how these methods would improve grip. Once the model is adequately trained on all aspects of road condition characteristics, it would be worthwhile to explore integrating RSC model input for real-time salt treatment. This could potentially enhance the overall effectiveness of the salt treatment strategy. For the manual mode experiment, the weather conditions were consistent, with a mix of sleet and snow before and after salt treatment. Consequently, grip improvement was insignificant, with the overall grip changing from 0.58 to 0.59. A total of 3,752 pounds of salt were used in this mode. In general, manual mode is not commonly used for MassDOT salt treatments. It is typically used only during heavy winter storms or challenging road conditions. In most cases, auto-grip mode is preferred.

For the salt rate model mode experiment, the weather conditions were a mix of sleet and snow before salt treatment, followed by moderate snow after treatment. The overall grip improved from 0.59 to 0.62. Of the three treatment modes, only the salt rate model mode resulted in an overall grip improvement below 0.60. According to the Vaisala grip description, a grip level 0.60 indicates moderate road grip. In real-time road treatments, the salt rate model spread the least amount of salt, totaling 2,369 pounds, compared to the other two methods, improving the overall grip. If auto-grip mode had been used for salt treatment in the same weather environment, the total salt would have been 3,453 pounds, resulting in an overuse of 1,084 pounds.

Based on the real-time validation and simulation testing analysis, the salt rate model performed well in grip improvement and salt usage efficiency. Real-time validation showed a grip improvement of 0.03 with a minimum salt usage of 2,369 pounds compared to the auto-grip and manual methods. The simulation experiment on the salt rate prediction model showed a reduction of approximately 18% in salt usage compared to the auto-grip mode. Conversely, the auto-grip mode showed a notable increase of 45.8% in salt usage compared to the salt rate prediction model.

3.4 Influence of the RSC's Accuracy

The impact of incorrect predictions made by the RSC model on the salt rate calculated by the salt rate prediction model and methods to mitigate mispredictions or inaccuracies generated by the RSC model are discussed in this section.

3.4.1 Impact of RSC Model on Salt Rate Prediction

Road surface misclassification can significantly impact salt rate calculations. The accuracy of the RSC model's classifications can be assessed using the confusion matrix in Figure 3-11, generated by the RSC model when tested on the testing data set.

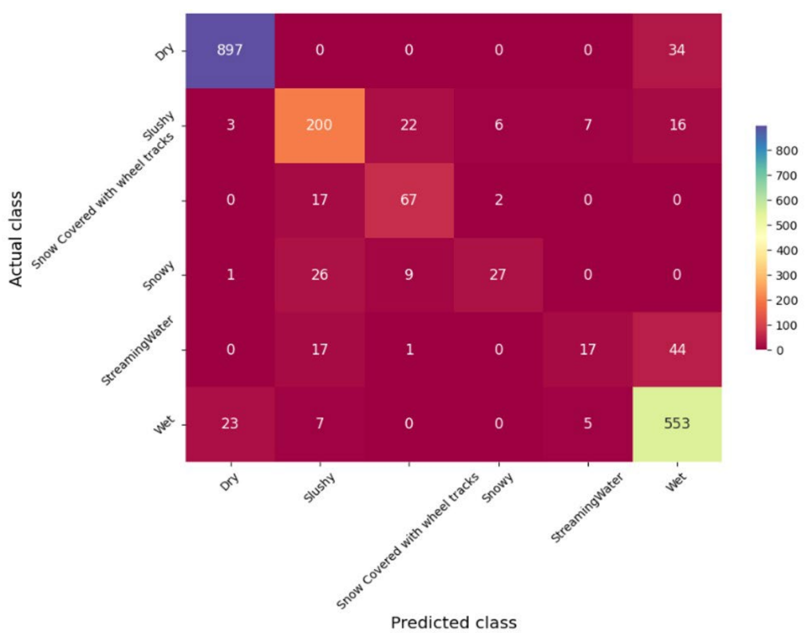


Figure 3-11: RSC model's confusion matrix

The matrix shows the number of times the model's predictions matched the actual conditions (values along the diagonal) and the number of times the model was incorrect (values off the diagonal). For example, the model is highly accurate in predicting "Dry" and "Wet" conditions, with 897 and 553 correct predictions, respectively. The model has moderate accuracy for "Slushy" and "Snow-covered with wheel tracks" conditions, with 200 and 67 correct predictions, respectively. However, "Snowy" and "Streaming water" road conditions have fewer testing instances, resulting in 27 and 17 correct predictions, respectively. Table 3-1 provides a detailed analysis of how mispredictions by the RSC model would impact salt rate calculations in the salt rate prediction model.

Out of all dry surface images, approximately 97% are correctly identified as dry by the RSC model. However, 0.32% of dry images are misclassified as slushy, 0.11% snowy, and 2.49% wet. Consequently, if a dry image were misclassified as wet, 65 lb/mi would have been overestimated compared to the actual salt rate. Similarly, dry images may be classified as snowy, but snowy conditions have varying salt rates based on MD30 grip values. For dry surfaces misclassified as snowy under grip conditions greater than 0.50, the predicted salt rate is 200 lb/mi, resulting in a 75 lb/mi overestimation. However, for grips lower than 0.50, the predicted rate ranges from 250–300 lb/mi, leading to overestimating 150 lb/mi. If the grip falls below 0.40, the overestimation reaches 212 lb/mi.

- According to the confusion matrix, if an image is misclassified as slushy, the average overestimation across different grip levels can be 225 lb/mi. However, very few images are misclassified as snowy or slushy, as indicated in the confusion matrix.
- According to the confusion matrix, 82.64% of slushy surface images are correctly classified as slushy. Among the remaining slushy images, 9.09% are misclassified as snow-covered-wheel-track surfaces, 2.48% as snowy, 2.89% as streaming water, and 2.89% as wet surfaces.

When slushy is misclassified as wet, the predicted salt rate ranges from 180–200 lb/mi, resulting in an underestimation of 110 lb/mi. If slushy is misclassified as snowy, there is an average underestimation of 79 lb/mi under different grip levels. In the misclassification of the slushy surface into snow-covered with wheel tracks surface, there is an underestimation of 25 lb/mi under grip conditions greater than 0.50. However, under grip conditions below 0.50 or 0.40, the salt rate prediction remains the same, even with the misprediction, as both surfaces fall under the same slippery category.

Similarly, if slushy is mispredicted as streaming water under grip conditions greater than 0.50, there is no difference in salt rate prediction. This is because slush and streaming water require the same treatment with equal salt rates under such grip conditions. Hence, this misprediction does not impact salt rate calculation. Similarly, Table 3-1 comprehensively analyzes how mispredictions for dry, wet, streaming water, snowy, slushy, and snow-covered-wheel-track surfaces affect salt rate calculations in the salt rate prediction model.

Table 3-1: RSC model misprediction impact on salt rate prediction

Road Condition	Predicted Condition	MD30 Condition	Actual Rate (lb/mi)	Predicted Rate (lb/mi)	Rate Difference (lb/mi)
Dry	Wet	0.50≤grip<0.80	100–150	180–200	65
Dry	Snowy	0.50≤grip<0.80	100–150	200	75
Dry	Snowy	0.40≤grip<0.50	100–150	250–300	150
Dry	Snowy	0.30≤grip<0.40	100–150	325–350	212
Dry	Slushy	0.50≤grip<0.80	100–150	300	175
Dry	Slushy	0.40≤grip<0.50	100–150	350	225
Dry	Slushy	0.30≤grip<0.40	100–150	400	275
Slushy	Wet	0.50≤grip<0.80	300	180–200	−110
Slushy	Snowy	0.50≤grip<0.80	300	200	−100
Slushy	Snowy	0.40≤grip<0.50	350	250–300	−75
Slushy	Snowy	0.30≤grip<0.40	400	325–350	−63
Slushy	SCWWT*	0.50≤grip<0.80	300	250–300	−25
Slushy	SCWWT	0.40≤grip<0.50	350	350	0
Slushy	SCWWT	0.30≤grip<0.40	400	400	0
Slushy	Streaming water	0.50≤grip<0.80	300	300	0
SCWWT*	Snowy	0.50≤grip<0 .80	250 –300	200	−75
SCWWT	Snowy	0.40≤grip<0.50	350	250–300	−75
SCWWT	Snowy	0.30≤grip<0.40	400	325–350	−63
SCWWT	slushy	0.50≤grip<0.80	250–300	300	25
SCWWT	Streaming water	0.50≤grip<0.80	250–300	300	25
Snow	SCWWT	0.50≤grip<0.80	200	250–300	75
Snow	SCWWT	0.40≤grip<0.50	250–300	350	75
Snow	SCWWT	0.30≤grip<0.40	325–350	400	63
Snow	Slushy	0.50≤grip<0.80	200	300	100
Snow	Slushy	0.40≤grip<0.50	250–300	350	75
Snow	Slushy	0.30≤grip<0.40	325–350	400	63
Streaming water	Slushy	0.50≤grip<0.80	300	300	0
Streaming water	Slushy	0.40≤grip<0.50	250–300	350	75
Streaming water	Slushy	0.30≤grip<0.40	325–350	400	63
Streaming water	Wet	0.50≤grip<0.80	300	180–200	−110
Wet	Dry	0.80≤grip ≤0.82	180–200	100–150	−65
Wet	Streaming water	0.50≤grip<0.80	180–200	300	110
Wet	slushy	0.50≤grip<0.80	180–200	300	110
Wet	slushy	0.40≤grip<0.50	180–200	350	160
Wet	slushy	0.30≤grip<0.40	180–200	400	210

* SCWWT: Snow-covered with wheel track.

In general, if a dry road condition is misclassified as wet, snowy, or slushy, if a wet road condition is misclassified as streaming water or a slushy road condition, or if a snowy surface is misclassified as snow-covered with wheel tracks or slushy, then the predicted salt rate estimation would be higher than the actual salt rate required. Conversely, misclassifying slushy surface conditions into snowy, wet, or snow-covered road conditions with wheel tracks would lead to a lower predicted salt rate estimation than the actual salt rate. If a snow-covered with wheel track surface condition is misclassified as slushy or streaming water, then the predicted rate estimation would be slightly higher (25 lb/mi) than the actual salt rate. Conversely, if it is misclassified as snowy, the predicted salt rate would be lower than the actual salt rate required.

No model can achieve 100% accuracy. However, the confusion matrix indicates that inaccuracies can be mitigated by implementing appropriate logical conditions between MD30's road condition parameter and the RSC model output to determine the correct road condition.

3.4.2 Sensitivity of the RSC Model on Salt Rate Prediction

The algorithm uses the prediction flowchart to assess grip and surface temperature conditions before determining the salt rate. Subsequently, it examines surface identification using input from the MD30 sensor and the RSC model. The surface identification process involves compiling input from the MD30 sensor and the RSC model using an OR condition. The sensitivity of the RSC model on salt rate prediction was evaluated by comparing the results obtained using both AND and OR conditions on the MD30 surface state inputs and the RSC model output for road surface classification.

Figure 3-12 displays the total salt used for salt treatment when using the salt rate prediction flowchart with and without RSC model input. The MD30 and RSC input utilize the AND logical condition for surface state identification. The dotted blue lines indicate a total salt usage of 2,898 pounds when using only MD30 input. The green dotted line represents a total salt usage of 2,790 pounds when incorporating MD30 and RSC model input under the AND logical condition, a reduction of 108 pounds.

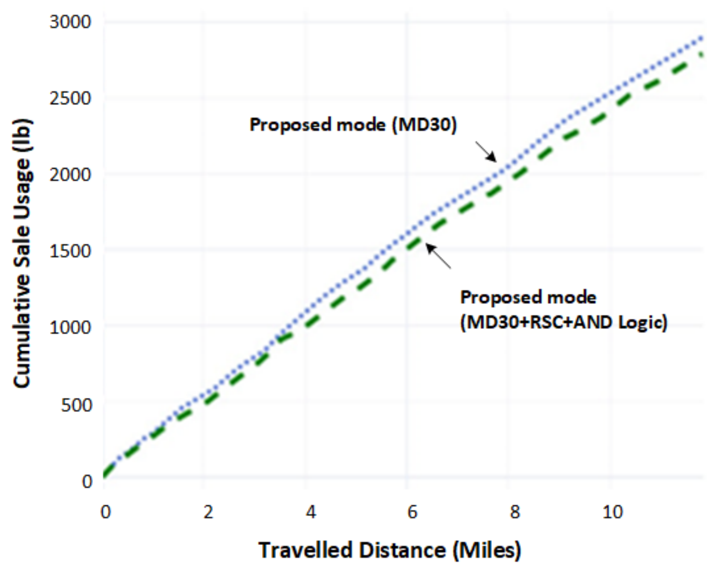


Figure 3-12: Total salt usage by the salt rate prediction model with AND condition

Similarly, Figure 3-13 illustrates the total salt used for salt treatment with the same inputs but under an OR condition. The dotted blue line depicts a total salt usage of 2,898 pounds with MD30 input alone. In comparison, the green dotted line indicates a total salt usage of 2,946 pounds when both MD30 and RSC model inputs are considered under the OR logical condition, increasing the salt usage by 48 pounds.

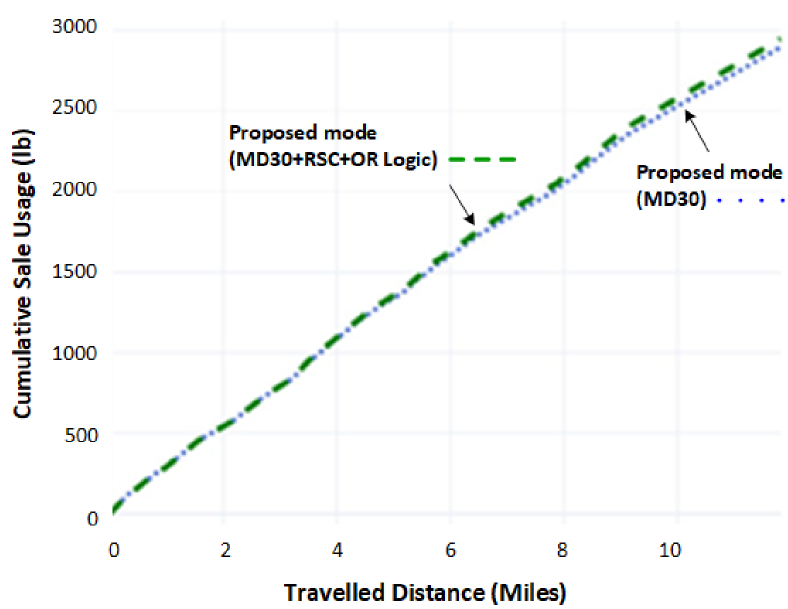


Figure 3-13: Total salt usage by the salt rate prediction model with OR logical condition

As mentioned earlier in this chapter, the RSC model is not 100% perfect in classifying road surfaces. Using the OR logical condition mitigates potential misclassifications made by the RSC model. Therefore, even though the total salt usage is higher when using the OR logical condition compared to the AND logical condition, it is preferable to err on caution. It is better to slightly overestimate salt usage than to risk missing important road conditions such as icy or slushy surfaces.

3.5 Limitations of the Developed System

- **Identification of Streaming Water Road Condition:** The RSC model, a key component of the salt rate prediction model, is trained to identify various road conditions such as dry, wet, snowy, snow-covered with wheel tracks, streaming water, and slushy. However, as reported in the previous chapter, an evaluation of the RSC model reveals that its precision–recall performance for identifying streaming water road conditions is poor. This poor performance stems from the limited number of images to train the model to recognize this particular road condition. Streaming water conditions are particularly challenging to identify because they occur when slush melts. If the surface temperature drops below freezing, the water can freeze into ice, reducing road traction. Accurately identifying streaming water conditions is essential for maintaining road safety and effectiveness. However, the RSC model faces challenges in correctly identifying these conditions. These limitations affect the overall effectiveness of salt treatment using the salt rate prediction model. The RSC model should be enhanced by collecting additional image data specifically targeting streaming water road conditions to address this issue. This expanded data set can then be used to retrain the RSC model, improving its ability to identify streaming water conditions accurately and thereby enhancing the effectiveness of the salt rate prediction model.
- **Night-Time Salt Treatment with RSC Model Input:** The current RSC model cannot be effectively utilized for nighttime salt treatment scenarios because the model was exclusively trained on daytime images. These images offer clarity and distinctiveness, making them suitable for training purposes. Nighttime images present challenges due to reduced visibility and illumination. Consequently, there is a risk of mislabeling nighttime images as snowy or slushy due to darkness. Although a lamp is near the camera to provide some illumination, the captured images remain visually unclear and inadequate for accurate classification. One potential solution to this issue involves using multiple illumination sources near the camera. Strategically placing additional light sources to cover the area captured by the camera can improve image clarity and detail. With clearer images, it becomes easier to accurately label road conditions and retrain the model for improved performance.
- **Black Ice and Packed Snow Detection:** The initial problem statement for this research was centered around the MD30 sensor's inability to detect black ice or packed snow, both of which present significant traction challenges. However, specific images of these road conditions could not be captured due to limited winter storm occurrences and fewer snow showers during the data collection. Consequently, the current RSC model cannot identify black ice and packed snow road conditions. In the next phase of the study, these specific road conditions will be targeted and incorporated into the model. An approach may involve collecting additional data and retraining the model to encompass black ice and packed snow classifications. The model's effectiveness for salt treatment can be enhanced by doing so.

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4.0 Conclusions

This project aims to develop an intelligent salt spreader system that effectively and efficiently delivers the appropriate rate of salt dispersal under specific road conditions and environmental factors. The approach presented eliminates the need for subjective analysis of road surface conditions. To achieve this objective, a salt spreader system has been developed through hardware integration, software development, algorithms development, and model development.

Previous research was analyzed to identify environmental factors affecting the salt rate. The RSC model provides surface conditions from captured pavement images to eliminate the need for visual monitoring. Additionally, the SRP model utilizes data from an RWIS sensor, including grip, surface temperature, surface conditions, and surface condition information from the RSC model, to predict the appropriate salt rate.

The research team developed a new salt application system in this study by leveraging the instrumented mobile RWIS (i.e., Vaisala MD30 sensor), computer vision, and a new salt application model. The research team focused on developing four key aspects of the intelligent salt application system, including hardware (i.e., data collection I/O and power supplies system), software (i.e., data logging, synchronization, and data fusion), algorithm (i.e., road surface classification [RSC] algorithm), and model (i.e., the salt rate prediction [SRP] model), so that an optimized salt application decision can be provided to the actuator to treat the road surfaces. Through this study, a complete hardware/software system with automated RSC and SRP algorithms has been developed, pilot-tested, and validated with promising performance.

Experimental tests during winter weather events facilitated an analysis of the salt rate prediction model and an evaluation of the efficiency of auto-grip mode, manual mode, and a salt treatment mode, which uses rates recommended by the salt rate prediction model. Further analysis was performed using simulation under fixed weather conditions. A comparative analysis of the results derived from all experiments was performed based on grip improvement and salt usage. The salt rate prediction model outperformed both auto-grip mode and manual mode.

- The research team explored the full integration feasibility of a mobile RWIS sensor, high-resolution camera, GPS, and Geotab logger and developed prototype software for comprehensive data collection.
- The research team developed an automated road surface classification algorithm using the DenseNet121 deep-learning model with an 86.7% accuracy.
- The research team integrated the detailed road surface classification outcome, the key parameters from the mobile RWIS sensor with a comprehensive salt rate decision tree that can potentially save salt applications by approximately 34% and 37%, compared with the auto-grip mode and the manual mode, while maintaining the similar performance of the treatment (i.e., maintaining or improving the grip values). The performance of the developed system showed promising results and could potentially save a significant amount of salt once implemented in a larger fleet of MassDOT's winter operations.

The salt rate prediction model simulation revealed an approximately 18% decrease in salt usage compared to auto-grip mode. The salt rate prediction model demonstrated efficient performance through cumulative results analysis, particularly during use under moderate to heavy weather conditions and sleet mixed snow weather conditions.

For future studies, the RSC model's capabilities should be enhanced to improve the salt rate prediction model further. More road condition categories (e.g., black ice and packed snow) and more road image examples could be considered. The RSC model's functionality should also be extended to consider nighttime road condition identification for nighttime salt treatment. Additional factors such as surface temperature gradient (increasing or decreasing) and the type of winter storm events anticipated, including light, medium, and heavy snow, sleet, black ice, or freezing rain, should be considered to improve the overall performance of salt treatment further. These factors can significantly impact the salt rate required for effective road treatment. They should be considered alongside surface grip, road condition, and surface temperature when determining the appropriate salt rate.

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6.0 Appendices

6.1 Hardware Connection Tutorial

6.1.1 MD30 Configuration and Connection

The MD30 is connected to the local data logger (LDL) using RS232 communication via a USB port. The MD30 sensor uses five RS232 wires for communication, as shown in Figure 6-1. Three wires are used for data transfer, and two are power and ground.

1. 115,200 bps
2. 8 data bits
3. 1 stop bit
4. No parity
5. No hardware controls

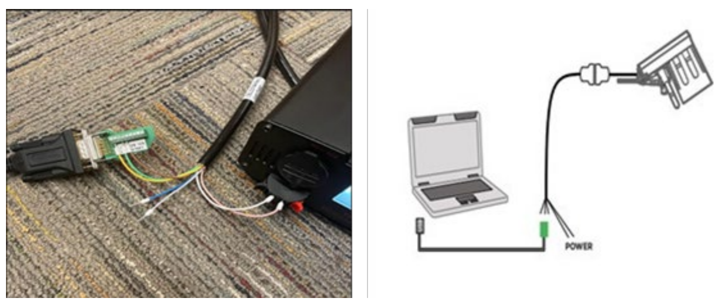


Figure 6-1: MD30 interface with the LDL

Table 6-1 shows the MD30 pin connection to the RS232 interface. An external power supply of 12 Volts is used for power. For initial MD30 communication testing, the open-source serial terminal software (OpenSerialPortMonitor—v1.0.5988.23754) was installed on the LDL. The MD30 sensor unit interface applies a request-response pattern. The sensor acknowledges every message. The following basic default settings must be configured on the LDL's serial terminal software to support RS232 communication.

Table 6-1: MD30 to RS232 pin description

Pin color	RS232/Power
Pink	Vin+
White	Vin−
Yellow	GND (RS-232)
Green	TX (RS-232)
Brown	RX (RS-232)

Once hardware setup and default settings are configured in the serial terminal application, communication is verified by sending a command to the MD30. A command for product info or unit ID can be sent to the MD30 to check communication. The following hex request is written in the “Data to send” section on the serial terminal application’s graphical user interface (GUI), as shown in Figure 6-2. A request message for product info is the following:

<message start ><message sender ID ><message receiver ID ><message ID ><message number><data length ><data ><CRC>

Ex. 0xab 0x00 0x01 0x11 0x02 0x00 0x00 0x32 0xa7

While sending the hex command to the sensor, “Data format” is selected. The “Send” option is then selected using a click. Figure 6-2 shows the MD30 response in the “Received data” and the “Raw data” window. Some command responses do not decode properly in the “Received data” window, but it is possible to verify raw data values using manual descriptions.

<message start ><message sender ID ><message receiver ID ><message ID ><message number ><interface version number><error code ><data length ><number of pairs and key-value pairs and values ><CRC >

The request response to the request is highlighted in Figure 6-2.

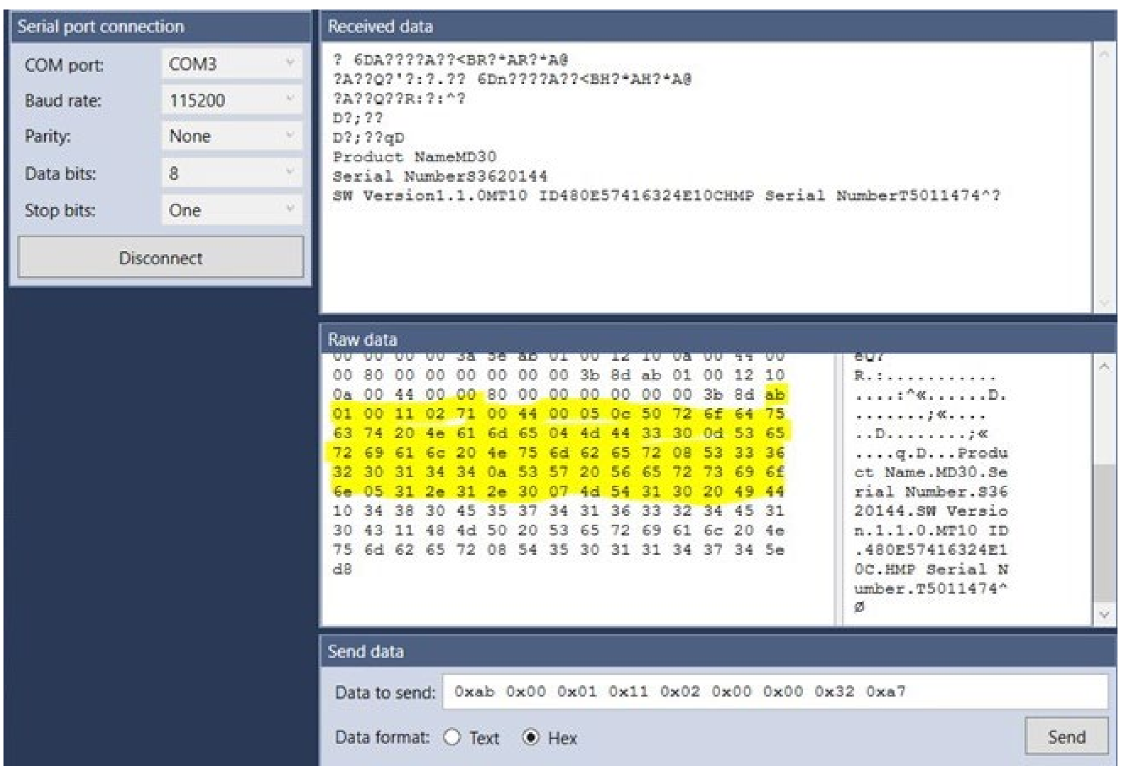
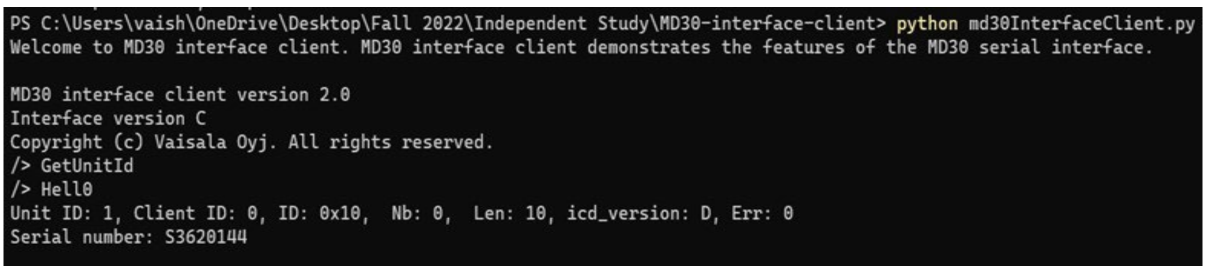


Figure 6-2: Verified communication on serial terminal application

MD30 responses use scripts and the mobile road sensor interface. To use the md30Interface client, the following system requirements should be fulfilled:

1. Windows 10 system
2. Any Python version above 3.7.3
3. PySerial module

Once the above requirements are met and the Python application and module are installed, all MD30 source code files should be copied to a folder on the LDL. The command prompt is opened from that location, and the interface client code file is called, which allows the MD30 to communicate with the LDL, as shown in Figure 6-3.



```
PS C:\Users\vaish\OneDrive\Desktop\Fall 2022\Independent Study\MD30-interface-client> python md30InterfaceClient.py
Welcome to MD30 interface client. MD30 interface client demonstrates the features of the MD30 serial interface.

MD30 interface client version 2.0
Interface version C
Copyright (c) Vaisala Oyj. All rights reserved.
/> GetUnitId
/> Hell0
Unit ID: 1, Client ID: 0, ID: 0x10,  Nb: 0,  Len: 10, icd_version: D, Err: 0
Serial number: S3620144
```

Figure 6-3: Calling interface client software to start communication

Vaisala has provided a variety of interface functions to calibrate and obtain the required information from the MD30 sensor. The MD30 module is programmed to record information/parameters received after the "SEND DATA" command is sent to MD30.

1. GET UNIT ID: Help to identify the installed unit.
2. GET FULL PRODUCT INFO: Provide brief information about MD30.
3. GET UNIT STATUS: Report status and error information.
4. SEND DATA: Initiate road condition, temperature, and humidity data reporting continuously at a defined interval.
5. GET PARAMETER: Get values for road and air temperature calibration.
6. SET PARAMETER: Set offset of the road and air temperature.
7. SET REFERENCES: Use to set reference values.
8. SET ROAD COEFFICIENTS: Use to set road coefficient values.
9. RESTART UNIT: Restart the sensor.
10. STOP REFERENCE SETTING: Used to interrupt reference data collection.

6.1.2 Camera Configuration and Connection

The project utilizes a Spinnaker FLIR camera, which communicates with the LDL via USB. For initial testing, the SpinView 3.0.0.118 application was used. To configure the programming module for the camera, the Spinnaker Python library module "spinnaker python3.0.0.118-cp310-cp310-win amd64.whl" was installed. This module depends on pip, NumPy, matplotlib, and pillow, which were installed.

The Spinnaker library was imported into the project as "pyspin." During the installation process, care was taken to ensure compatibility between the Spinnaker library version and the Python version being used. Because Python version 3.10 was used, the appropriate Spinnaker library "spinnaker /python-3.0.0.118-cp310-cp310-win amd64.whl" was installed in this case. This camera module can capture pavement images, name them, and store them on disk. Image names are stored in a CSV file. Figure 6-4 shows a screenshot of the SpinView application for camera testing. The research team integrated all the functions from the SDK into the main software, while the SpinView application was solely for calibrating camera purposes.

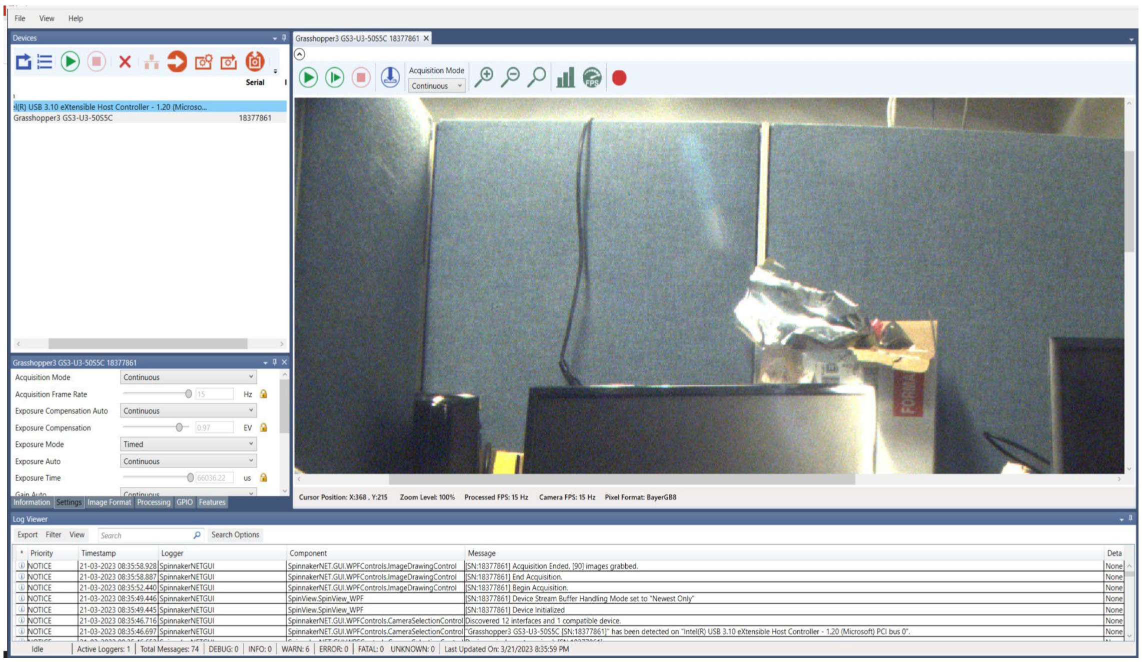


Figure 6-4: SpinView application for testing camera

6.1.3 GPS Configuration and Connection

The Xsens motion tracker device is utilized for GPS. The Xsens device features an inertial measurement unit (IMU) and an integrated GNSS receiver, which acts as an antenna and enables the determination of location coordinates. The Xsens device also offers real-time visualization capabilities. It allows users to view the 3D orientation of the system, monitor data from both the inertial and magnetic sensors, and track latitude, longitude, and altitude in real-time.

For system setup, the Xsens module is only used for GPS. GPS values are communicated to the LDL using USB. For initial testing, Xsens MT Manager 2022 was used. The Xsens application records its parameters into .mtb and .csv files. However, I developed a separate program to log GPS data into larger CSV files, as MD30, GPS, and camera data are needed in a single file. To program and interact with the Xsens device, use a dedicated library called xsensdeviceapi-2022.0.0-cp310-none-win amd64.whl. Before installing this library, it was necessary to ensure the presence and proper functioning of the wheel library module. The version of Python used must be compatible with the Xsens library, in this case, Python 3.10. Once the Xsens library was successfully installed, it was imported as xsensdeviceapi.xsensdeviceapi_py310 64. The GPS module is programmed to record the longitude and latitude values along with its time stamp.

6.2 Tutorial for Local Data Logger (LDL) Configuration

6.2.1 LDL Configuration for the UMass Vehicle

This experiment tested the LDL using inputs from the MD30, a GPS device, and a camera. The testing functions verify the (1) correctness of file logging (e.g., formatted csv file at 1 record/second including all MD30 readings, GPS coordinates and GPS time, camera frame number, and file name); (2) synchronization of the data (e.g., camera and MD30 data synchronization); and (3) reliability of logger functionality (e.g., duration, storage, etc.). This experiment required sensor and configuration, host computer installation, monitor, cabling, and so forth, and vehicle hardware mounting. It was performed on dry and wet surfaces.

- A sport utility vehicle (SUV) owned by UMass was used for testing. Initially, the research team attached a hitch to the UMass vehicle to install the MD30. Subsequently, a flexible and adjustable assembly was created with mounting brackets and plates, allowing for easy attachment and detachment from the vehicle as needed. Figure 6-5(a) shows the MD30 mounting on the SUV.
- For the GPS component, the Xsens Motion Tracker system was utilized. It consists of a control unit and an antenna. The control unit was installed inside the vehicle and connected to the LDL, while the antenna, which has a magnet, was attached to the roof, as shown in Figure 6-5(b).
- A FLIR Spinnaker camera was used in the experiments. For secure mounting, the camera was installed in the trunk with the help of a screw shown in Figure 6-5(c). The camera could capture the road surface from the trunk's transparent window.
- The UMass vehicle already had inverters in the trunk that could power components. The inverter features two three-pin plugs: one connected to the 12-volt power supply regulator, while the other powered the CPU. The 12-volt power supply was utilized to power the MD30 sensor. Once the CPU was powered, a touchscreen display, GPS, and camera were connected. This setup ensured the CPU, display, MD30, GPS, and camera received the necessary power to function. Figure 6-5(d) shows the overall SUV setup.

(a) MD30 mounting on the UMass vehicle (b) GPS antenna placement

(c) Camera mounting on a SUV (d) Overall assembly of the UMass vehicle

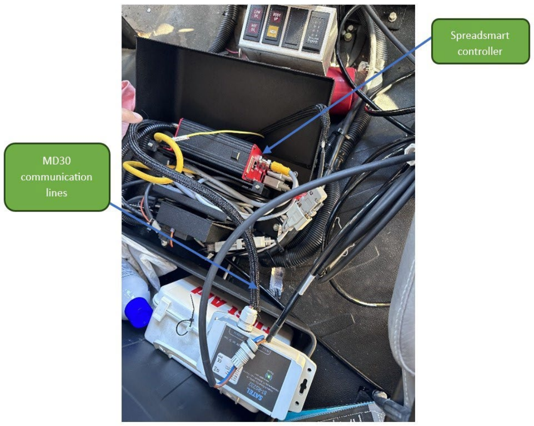
Figure 6-5: Installed sensors on the UMass vehicle

6.2.2 LDL Configuration for the MassDOT Truck

The configuration of the LDL for the MassDOT Truck focused on setting up dual communication between SpreadSmartRx and the LDL. It also validated data logging from the MD30, a camera, and a GPS device mounted on a MassDOT plow truck. Additionally, it verified the salt rate (i.e., SpreadSmartRx data) logged on the Geotab fleet management service running on the MassDOT truck. This experiment aimed to test the functionality of two loggers: a local data logger that recorded MD30 parameters, captured images, and GPS coordinates; and a Geotab logger capturing salt rate with time stamps and GPS coordinates.

Figure 6-6: MassDOT truck STL942

- The MassDOT truck STL942, shown in Figure 6-6 and Figure 6-7(a) (cabin), was designated to the research team in District 3. The MD30 and a SpreadSmartRx controller were already installed on the truck. The MD30 is located on the front of the truck, as shown in Figure 6-7(b). The SpreadSmartRx controller is placed in the driver's cabin. As shown in Figure 6-7(a), the SpreadSmartRx controller is kept beneath the black box, and the MD30 is connected to the SpreadSmartRx controller through an RS232 communication line.
- After discussing with the MassDOT plow operator, the camera was positioned near the spreader assembly on the truck's rear side, as shown in Figure 6-7(c). This location allows the camera to capture the road view without interfering with the truck's operation or obstructing the driver's view. To get a broader view of the road, wide angle lenses were used to get a broader field of view for the road.
- The same GPS setup as Experiment 1 was utilized. For GPS, antenna position is important. The antenna must be outside to receive signals. The antenna was attached near a door handle. As shown in Figure 6-7(d) (highlighted by red arrow), the cigarette lighter port was used to power the inverter and subsequently power the LDL.
- For this experiment, it was necessary to establish the MD30's connection with LDL, the GPS connection, the camera installation, and the inverter connection to power LDL in the truck's cabin.



(a) MD30 connection to SpreadSmartRx

(b) MD30 placement on the truck

(c) Camera setup on the MassDOT truck

(d) Power Supply

Figure 6-7: Installed sensors on the MassDOT Truck

6.3 Tutorial for Data Collection

6.3.1 Data Logging Using the UMass vehicle

For the data logging using the UMass vehicle, all the tests for the data collection were performed on the UMass vehicle operating at a maximum speed of 25–30 mph. Data was collected on wet and dry roadways and parking lots in Amherst, MA, and on the UMass Amherst campus. Figure 6-8 and Figure 6-9 display snippets of the collected data. During data collection, MD30 parameters, GPS coordinates, time stamps, and the names of captured images were stored in a CSV file. MD30 parameters include road surface state, EN15518 state, grip, and water level.

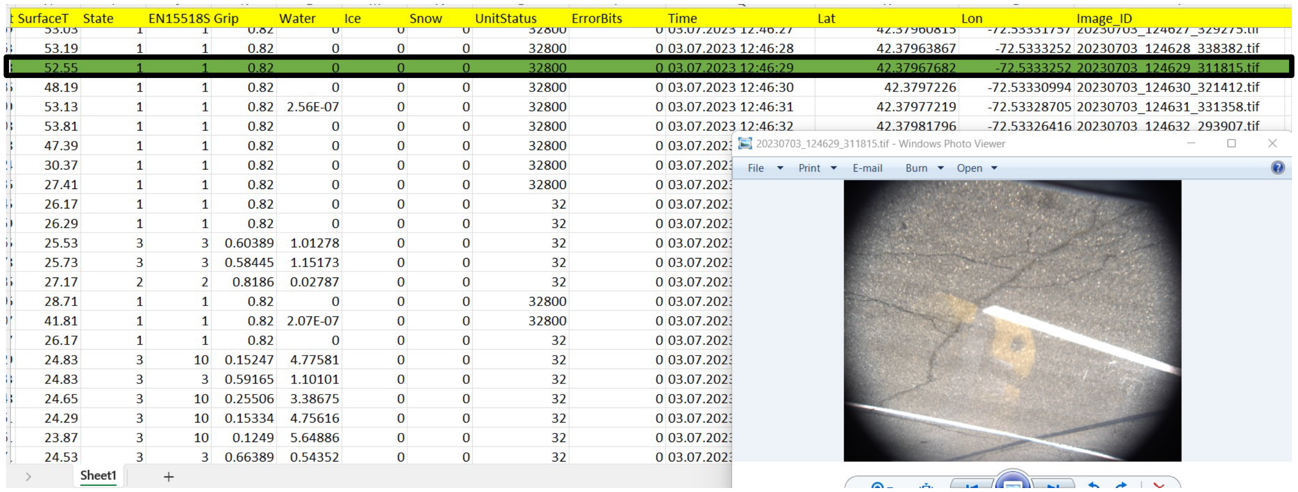


Figure 6-8: Detection example of the dry road surface

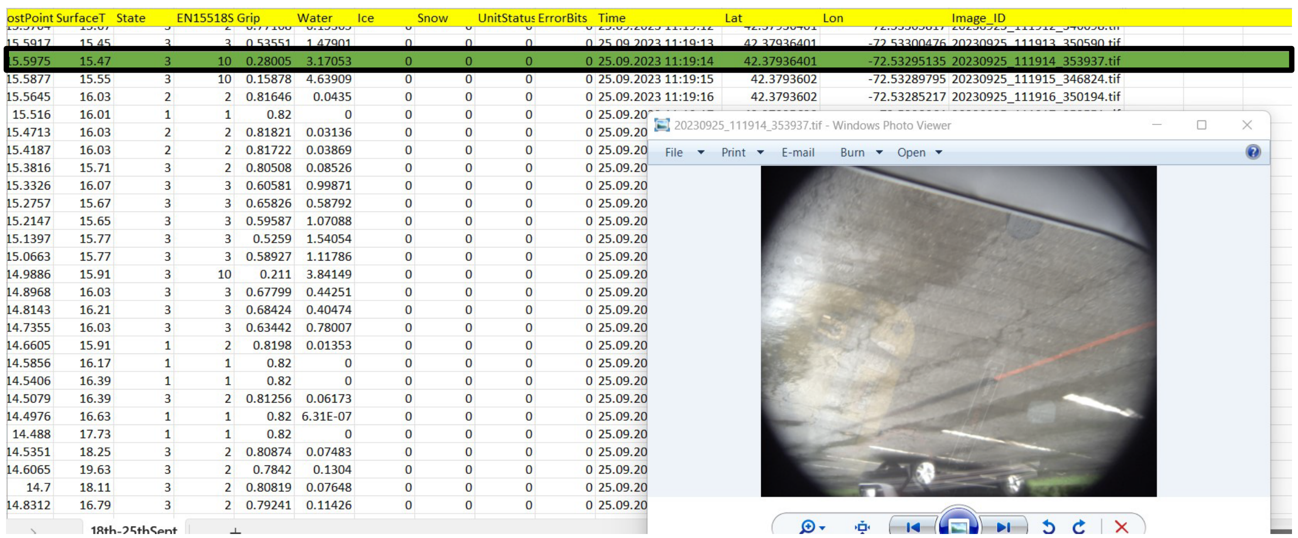


Figure 6-9: Detection example of the wet road surface

In Figure 6-8, the captured image displays a dry surface, and its corresponding MD30 values (highlighted in green and bordered in black) also indicate correct values for dry surfaces. For instance, the values for state and EN15518 are both 1, reflecting a dry state per the value description in Table 2-2. Additionally, the high grip value and the absence of water level (0 water level) further indicate a dry surface.

In Figure 6-9, the captured image reveals a watery surface, and its corresponding MD30 values (highlighted in green and bordered in black) accurately reflect wet conditions, per Table 2-2. The MD30's state value of 3 indicates wetness, and the EN15518's state value of 10 suggests streaming water. Additionally, a lower grip value of 0.28 and a water level of 3.17 mm further confirm the strong presence of water. The data quality and logger integrity were also tested in high-speed scenarios. Camera-captured images often have motion blur. To overcome this blur, the exposure rate/shutter speed was manipulated at the start of the experiment. Setting "Exposure Auto" to OFF adjusts the exposure time and reduces the exposure time to increase the shutter speed.

6.3.2 Data Logging Using the MassDOT Truck

For the data logging using the MassDOT truck, the MD30 is connected to the LDL and the SpreadSmartRx controller's "temp/GPS" port, shown in Figure 2-5, using RS232 communication. The controller is located in the driver's cabin. A Y splitter provided the MD30 signal to the LDL and the SpreadSmartRx controller (Figure 6-10). Initially, the LDL did not receive a response from MD30, and the SpreadSmartRx controller's protective fuse blew. Because RS232 is point-to-point communication, only one device drives an RS232 serial line. Effectively, both the LDL and MD30 were driving the signal.

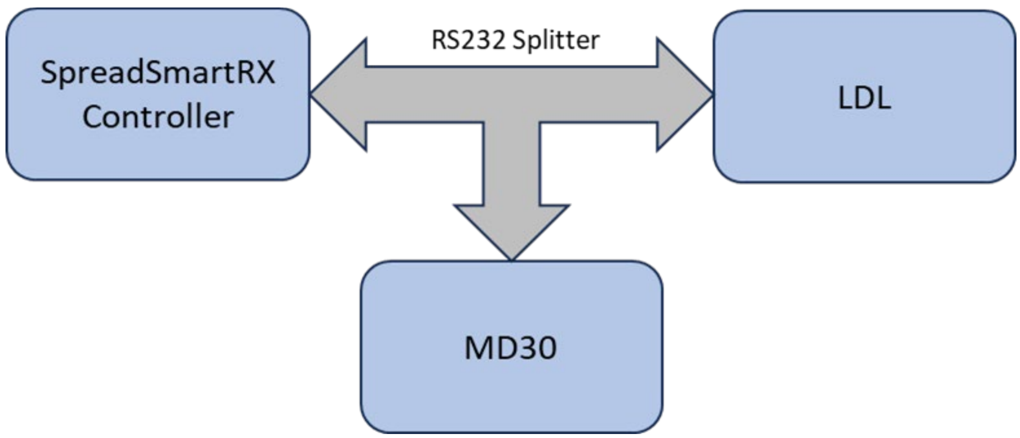


Figure 6-10: Y splitter connection

To establish passive (unidirectional) communication between the MD30 and the LDL, TX communication from the MD30 is needed. For passive communication, only TX and GND connections are needed. With this connection, the LDL only receives the data from the MD30. Laptop transmissions are ignored. To establish the connection described above, a customized RS232 cable was utilized. Figure 6-11 shows that the MD30's TX (transmitting) signal is carried on PIN 2, while the RX (receiving) signal is carried on pin 3. The LDL must listen to the MD30's transmitting line for a passive LDL port connection. In Figure 6-11, the TX signal on pin 2 must be connected to RX pin 3 of the LDL's port.

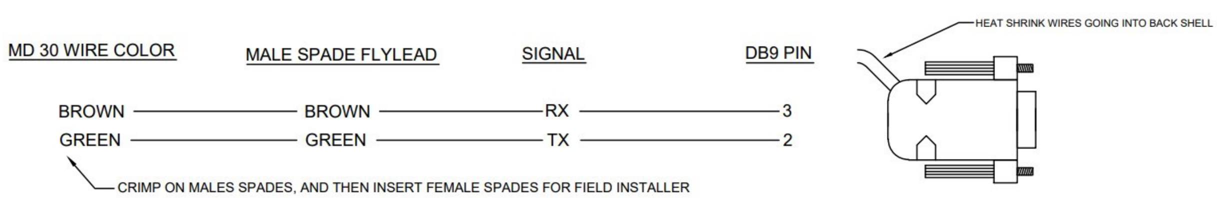


Figure 6-11: MD30 to SpreadSmartRx connection

Figure 6-12 shows the overall connection used in the truck, and the detailed pin connection can be found in Figure 2-8. An RS232 connector and an RS232 serial port cable were utilized. The brown-colored pin of the RS232 cable is connected to the RS232 connector's pin 3, and the yellow-colored pin is connected to pin 5.

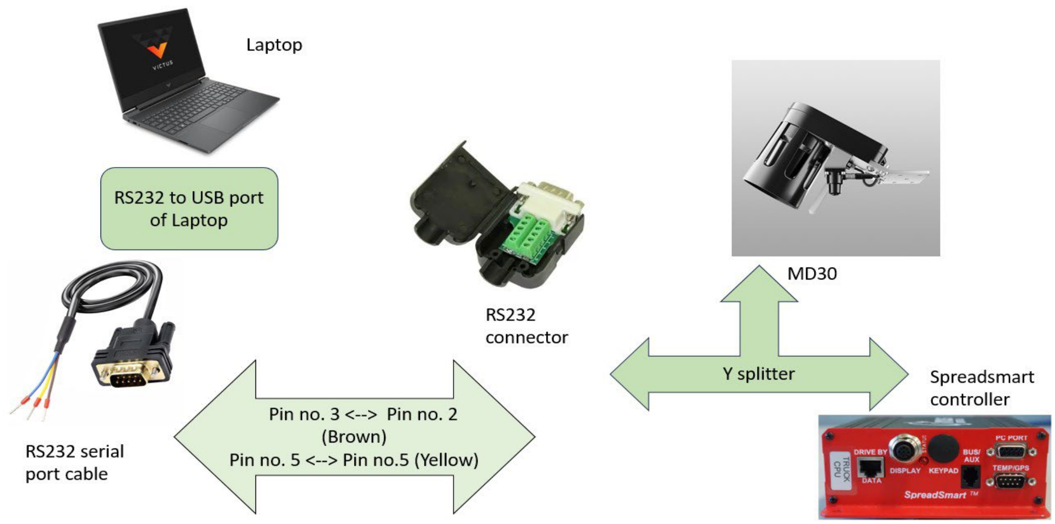


Figure 6-12: Connection setup block diagram

After successfully configuring the MD30 dual communication with the LDL, one may proceed to verify the logger's functionality, which records MD30 parameters, GPS, and camera frames. Synchronization between MD30 and camera data can be achieved as described in Sections 6.1 and 6.2. Figure 6-13 shows a snippet of the local log generated on the truck. It recorded all sensor values properly. This log converts the GPS timing signal to 12-hour values to create more precise time stamps.

In some cases, MD30 data was not stored due to data unavailability at specific time stamps. However, these occurrences were infrequent (15 instances of unavailable MD30 records in a data set of 1,200 data points). These unstamped instances were removed for further consideration using a Python program. Road surface images were captured on the truck using a wide-lens camera. Due to the wide lenses, the road surface and the housing edges were captured. Using a Python program, the images were cropped to obtain the proper road view, as illustrated in Figure 6-14. The Geotab logging mechanism was used for each run of the STL942 MassDOT truck. Logged information included time stamps, GPS coordinates, and the salt rate. Logging instances for the Geotab logger were verified while operating the MassDOT truck, and all sensors were mounted and utilized. Figure 6-15 shows the snippet of the Geotab log recorded during this test.

AnalyzeCo	DataWarn	DataError	AirT	RH	DewPoint	FrostPoint	SurfaceT	State	EN15518S	Grip	Water	Ice	Snow	UnitStatus	ErrorBits	Time	Lat	Lon	Image_ID	GPS_time
21055	2016	0	10.7600002	22.95000076	-9.57373	-8.50574	5.230011	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:11	42.20363235	-71.8139801	20231220_123011_6	12:30:11 PM
21059	2016	0	10.7600002	22.95000076	-9.57373	-8.50574	5.230011	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:12	42.20370865	-71.81391907	20231220_123012_1	12:30:12 PM
21065	2016	0	10.7600002	22.95000076	-9.57373	-8.50574	5.709991	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:12	42.2037735	-71.81386566	20231220_123012_6	12:30:12 PM
21069	2016	0	10.7600002	22.95000076	-9.57373	-8.50574	5.709991	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:12	42.20383835	-71.81381226	20231220_123013_0	12:30:12 PM
21073	2016	0	10.7600002	22.95000076	-9.57373	-8.50574	5.98999	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:13	42.20390701	-71.81375885	20231220_123013_6	12:30:13 PM
21077	2016	0	10.7600002	22.95000076	-9.57373	-8.50574	5.98999	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:13	42.20397568	-71.81370544	20231220_123014_1	12:30:13 PM
21081	2016	0	10.7600002	22.95000076	-9.57373	-8.50574	5.98999	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:14	42.20404434	-71.81365204	20231220_123014_6	12:30:14 PM
21086	2016	0	10.7600002	22.90999985	-9.59588	-8.52561	5.98999	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:15	42.20411301	-71.813591	20231220_123015_2	12:30:15 PM
21090	2016	0	10.7600002	22.90999985	-9.59588	-8.52561	6.570007	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:15	42.20418549	-71.8135376	20231220_123015_6	12:30:15 PM
21094	2016	0	10.7600002	22.90999985	-9.59588	-8.52561	6.609985	1	1	0.82	5.75E-07	0	0	32768	0	20.12.2023 12:30:15	42.20426178	-71.81347656	20231220_123016_0	12:30:15 PM
20.12.202	42.20433	-71.8134	20231220_1:	12:30:16 PM																
21713	2016	0	10.8299999	22.37999916	-9.83367	-8.73891	9.070007	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:16	42.20441818	-71.81335449	20231220_123017_0	12:30:16 PM
21718	2016	0	10.8400002	22.35000038	-9.84224	-8.7466	9.070007	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:17	42.20447922	-71.81330109	20231220_123017_5	12:30:17 PM
21722	2016	0	10.8400002	22.35000038	-9.84224	-8.7466	9.109985	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:17	42.20453644	-71.81325531	20231220_123018_0	12:30:17 PM
21726	2016	0	10.8400002	22.35000038	-9.84224	-8.7466	9.109985	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:18	42.20461273	-71.81319427	20231220_123018_4	12:30:18 PM
21730	2016	0	10.8400002	22.35000038	-9.84224	-8.7466	9.109985	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:18	42.20467758	-71.81314087	20231220_123018_9	12:30:18 PM
21736	2016	0	10.8400002	22.35000038	-9.84224	-8.7466	9.149994	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:19	42.20475006	-71.81307983	20231220_123019_4	12:30:19 PM
21740	2016	0	10.8400002	22.35000038	-9.84224	-8.7466	9.429993	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:19	42.20481873	-71.81302643	20231220_123019_9	12:30:19 PM
21744	2016	0	10.8400002	22.35000038	-9.84224	-8.7466	9.429993	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:20	42.20487976	-71.81297302	20231220_123020_5	12:30:20 PM
21748	2016	0	10.8400002	22.35000038	-9.84224	-8.7466	9.429993	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:20	42.20494843	-71.81291962	20231220_123021_0	12:30:20 PM
21753	2016	0	10.8400002	22.35000038	-9.84224	-8.7466	9.290009	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:21	42.20501328	-71.81286621	20231220_123021_4	12:30:21 PM
21757	2016	0	10.8400002	22.30999947	-9.86493	-8.76696	9.290009	1	1	0.82	0	0	0	32768	0	20.12.2023 12:30:21	42.20508575	-71.81280518	20231220_123021_8	12:30:21 PM

Figure 6-13: Data log generated on the MassDOT truck

(a) Original image

(b) Cropped image

Figure 6-14: Examples of the captured images

Log Data and Collisions Report

Massachusetts Department of Transportation

Device	Device Group	First Name	Date	Log Time	Record Type	Speed	Longitude	Latitude	Reason for Log	Ign
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:29:10 PM	GpsRecord	3	-71.81931	42.19820	CurveZeroSpeed	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:29:12 PM	GpsRecord	8	-71.81927	42.19817	CurveSpeedEstimateEr	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:29:15 PM	GpsRecord	11	-71.81911	42.19812	CurveSpeedEstimateEr	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:29:22 PM	GpsRecord	15	-71.81878	42.19827	CurvePositionEstimate	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:29:29 PM	GpsRecord	25	-71.81834	42.19873	CurveSpeedEstimateEr	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:29:36 PM	GpsRecord	33	-71.81773	42.19942	CurvePositionEstimate	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:29:45 PM	GpsRecord	38	-71.81678	42.20047	CurveSpeedEstimateEr	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:29:56 PM	GpsRecord	38	-71.81555	42.20193	CurveSpeedEstimateEr	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:30:25 PM	GpsRecord	42	-71.81207	42.20598	CurvePositionEstimate	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:30:36 PM	GpsRecord	48	-71.81061	42.20764	CurveSpeed	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:30:40 PM	GpsRecord	47	-71.81007	42.20828	CurvePositionEstimate	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:30:56 PM	GpsRecord	45	-71.80792	42.21077	CurveBased	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:31:02 PM	GpsRecord	46	-71.80698	42.21158	CurveSpeedEstimateEr	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:31:08 PM	GpsRecord	45	-71.80582	42.21225	CurvePositionEstimate	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:31:15 PM	GpsRecord	46	-71.80426	42.21279	CurvePositionEstimate	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:31:23 PM	GpsRecord	46	-71.80231	42.21307	CurvePositionEstimate	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:31:29 PM	GpsRecord	46	-71.80083	42.21302	CurvePositionEstimate	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:31:37 PM	GpsRecord	42	-71.79904	42.21264	CurvePositionEstimate	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:31:45 PM	GpsRecord	37	-71.79742	42.21220	CurvePositionEstimate	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:31:50 PM	GpsRecord	26	-71.79663	42.21197	CurveSpeedEstimateEr	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:31:54 PM	GpsRecord	14	-71.79623	42.21184	CurvePositionEstimate	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:31:58 PM	GpsRecord	2	-71.79610	42.21181	CurvePositionEstimate	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:31:59 PM	GpsRecord	0	-71.79610	42.21181	CurveZeroSpeed	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:32:01 PM	GpsRecord	0	-71.79610	42.21181	CurveSpeedEstimateEr	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:32:02 PM	GpsRecord	1	-71.79610	42.21181	CurveZeroSpeed	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:32:05 PM	GpsRecord	6	-71.79604	42.21179	CurveSpeedEstimateEr	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:32:11 PM	GpsRecord	17	-71.79572	42.21171	CurvePositionEstimate	
Auburn STL942	Vehicle, Diesel, UMass Stud		Dec 20, 2023	12:32:15 PM	GpsRecord	24	-71.79528	42.21158	CurvePositionEstimate	

Figure 6-15: Geotab logger generated on the MassDOT truck