FORECASTING WINTER ROAD CONDITIONS: A DATA-DRIVEN APPROACH

A Thesis

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by

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ABSTRACT

Annually, 24% of weather-related vehicle crashes happen on snowy, slushy, or icy roads in the United States. Accurate prediction of road surface temperatures and conditions is crucial for ensuring safe and efficient transportation, especially during winter. In this study, we developed machine learning and computer vision models for predicting road surface temperatures and conditions using historical meteorological and road surface sensor data and images. We implemented machine learning algorithms to build models that can predict road surface temperatures and conditions with high accuracy. We also developed computer vision models to detect real-time road surface conditions, including dry, wet, ice, snow, and slush, based on real-time road surface image data. Integration of temperature prediction models, surface condition prediction models, and computer vision models into existing road weather information system (RWIS) networks has the potential to provide accurate predictive information on road surface temperatures and conditions, enhancing the safety and efficiency of transportation systems, especially in rural communities where there are limited RWIS resources.

Keywords: winter, road surface temperatures, road surface conditions, computer vision, machine learning, Road Weather Information System

BIOGRAPHICAL SKETCH

The author, Jeswin Wilson was born in India but spent a very good part of his life in Kuwait. It was here while spending his summer holidays in the blistering heat, he found solace in books. He would read anything he could get his hands on. Through his literary explorations, he honed his discernment for quality writing, developing a refined taste in books. He ventured across various genres, authors, and styles, immersing himself in compelling narratives with nuanced themes and profound insights. Yet his literary journey didn't stop at fiction alone. His curiosity led him to non-fiction works, particularly those delving into the wonders of science. Science books captivated him, revealing the intricacies of the natural world and the marvels of the universe. He found themselves engrossed in scientific concepts, theories, and discoveries, feeding his innate sense of wonder, and sparking a thirst for knowledge.

This interest in science was smoothly woven into his academic endeavors, particularly as he started embarked on a bachelor’s degree in mechanical engineering from APJ Abdul Kalam Technological University in Kerala, India where he was particularly fascinated by the fields of computer-aided design and thermodynamics. He believes that the notion of perpetual motion machines was something that evoked a deep sense of awe in him when he first learnt about it, which later became the glue that has preserved his unwavering passion for the field over time.

This profound interest in mechanical engineering ultimately led him to a master's degree with a specific focus on energy and the environment, developing tools to help society in whatever little way he can. Nowadays, Mr. Wilson can be found enjoying the occasional game of football on weekends, while during the weekdays he's busy fending off his cat from typing essays on his keyboard.

To Sredha and Takito, my two bundles of joy.

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As I reflect on the past two and a half decades years of my life, I realize that I would not be anywhere close to where I am now without the unwavering support and guidance of numerous individuals, some with whom I'm still in touch, and some I regretfully am not. While I may not be able to name all of them in the confines of this section, the impact of their actions on me will continue to resonate in everything I do. I am deeply indebted to the individuals and organizations whose unwavering support and invaluable contributions have made this thesis possible.

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I would like to express my heartfelt appreciation to my parents and my younger brother for their unwavering love, support, and encouragement throughout my academic journey. Their selfless dedication, sacrifices, and belief in my abilities have been the foundation of my success. From the earliest stages of my education to the completion of this thesis, their constant presence and guidance have provided me with the strength and motivation to overcome challenges. Their unwavering belief in me has instilled the confidence to pursue my dreams. I am forever grateful for their unconditional love, unwavering support, and endless sacrifices that have shaped me into the person I am today. This achievement would not have been possible without them, and their impact on my life is immeasurable.

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LIST OF ABBREVIATIONS

Abbreviation	Expansion
RST	Road Surface Temperatures
RSC	Road Surface Conditions
RWIS	Road Weather Information Systems
CNN	Convolutional Neural Networks
PDE	Partial Differential Equation
IoT	Internet of Things
IR	Infrared Radiation
ML	Machine Learning
CV	Computer Vision
DOT	Department of Transportation
RMSE	Root Mean Squared Error
GFR	Game Farm Road
CCTV	Closed Circuit Television
MAE	Mean Absolute Error
MSE	Mean Squared Error
ROI	Region of Interest

CHAPTER 1

INTRODUCTION

The northern parts of the United States often experience winters that can be bitterly cold, with frequent lows well below zero degrees Fahrenheit. Driving in such conditions can be challenging, particularly on roads that are improperly maintained and susceptible to ice and snow. Road pavement conditions represent an important part of winter road maintenance operations. The road surface condition at a particular instant (dry, damp, wet, ice, or snow) in time helps the officials in determining the best course of action. Similarly, micro-forecasts of road conditions can help officials prepare well in advance to combat what is to come.

There are different methods by which the officials determine the condition of the road surface at a particular time. Officials often use visual inspection and surface auscultation for pavement inspection. Wireless sensor networks and machine learning models have been employed to monitor large stretches of roads. Road Weather Information Systems (RWIS) have been employed on long stretches of road throughout the country which provide vital information such as atmospheric, water level and pavement conditions over several intervals throughout the day [1], [2]. A road weather information system (RWIS) is a network of sensors that collect data on road weather conditions. This data can be used to improve safety and efficiency on the roads. RWIS systems typically collect data on air temperature, humidity, wind speed and direction, precipitation type and amount, visibility, pavement temperature, and pavement condition [1]–[4]. This data can be used to issue warnings about hazardous road conditions, adjust traffic signals to improve safety and flow, pre-treat roads with salt or sand to prevent icy conditions, dispatch snow ploughs and other snow removal equipment, and provide real-time information to drivers about road conditions [2][3]. RWIS systems can be a valuable tool for improving safety and efficiency on the roads and can help reduce accidents, improve traffic flow, and make the roads safer for everyone. However, RWIS systems can be expensive to install and maintain, and the quality of the data collected can vary depending on the location and the quality of the sensors.

The United States spends over $2.3 billion every year to combat snow/ice on the roads and over $5 billion a year to repair weather damage to roads, bridges, and sidewalks. Chemicals like sodium chloride are frequently used to melt ice and snow on roadways. These help in reducing the freezing point of water, preventing formation of ice, and preventing the melting of existing snow and ice [4]. Chemicals like sand or gravel are used to improve traction on roads by providing a rough surface for the tires to grip. These chemicals help in improving road safety while driving. Some of the adverse effects of excess salt on roads include the salinization of freshwater springs, algal blooms, corrosion of water pipes, and damage to small organisms [4]. Having better forecast techniques to reduce the amount of salt on roads can help both the environment and the economy.

The primary limitation of Road Weather Information Systems (RWIS) is their static positioning, which restricts the amount of road that can be monitored by a single station. The forecasts thus produced tend to be extremely localized and have limited coverage. When the weather changes or there are other unforeseen events like accidents or road closures, RWIS systems might not be able to immediately adjust. The sensors in an RWIS system are also subject to malfunctions and may require extensive manpower to repair and maintain. The high expenses related to RWIS stations are a significant concern, ~ \$100,000 to build and ~ \$20,000/year to repair and maintain[2][3][5] per RWIS station.

Municipalities often lack the resources to actively monitor road surface conditions (RSC) on their own. This limitation is primarily due to budgetary constraints, making it impractical for municipalities to manually inspect every camera in the city or hire contractors to regularly survey the entire road network [6]. The use of Machine Learning (ML) techniques can help achieve wider geographical coverage and more frequent updates. By incorporating ML, contractors, and staff responsible for surveying RSC will no longer be required to manually interpret the data. Their sole responsibility will be to capture road footage, eliminating a significant portion of the manual labor previously involved in obtaining RSC information.

There has not been a lot of work done in the field of road surface monitoring in which both the machine learning techniques, such as regression and classification are used in tandem to predict the road surface temperatures and conditions which is a research gap we aim to fill with the ideas in this paper. The proposed solution to increase road safety during winter months makes use of low-cost temperature sensors and neural network-based models to predict road surface temperatures (RST) and conditions (RSC) which will be explained in detail in the next few sections. Chapter 3 of this thesis will go in depth about road surface condition classification and predictions. This will help provide the public and the officials well in advance about the condition of the road surface which will enable better decision making and employment of preventative techniques to make winter roads safer to commute. Chapter 4 will go in detail about road surface temperature predictions which will be used in tandem with road surface condition predictions which will help decide on anti-icing techniques to be used. Chapter 5 will talk about employing image classifications models for detecting road surface conditions and Chapter 6 will be exploring a novel technique of detecting road surface temperature from images of roads collected from CCTV cameras.

We believe that addressing the cost and availability challenges of RWIS systems in rural communities is important because access to accurate weather information is crucial for various stakeholders, including farmers, emergency responders, and transportation agencies. By developing more affordable and accessible RWIS solutions, our work aims to bridge the gap and provide valuable weather information to rural and remote areas, thereby enabling better decision-making and enhancing the safety and well-being of those communities.

CHAPTER 2

METHODOLOGY

A very basic algorithm to be adopted for winter road conditions monitoring is to recognize the road conditions at a point in time and figure out the sensors and data sources that can be used to keep tabs on these conditions. The next step in that process would be to develop the hardware and software of the road monitoring tools and test it periodically by deploying it onto the field and analyzing data often. This data collected can then be implemented into a larger system to provide drivers with real-time information about road conditions. This tool must be continuously monitored and re-calibrated to ensure its accuracy and reliability.

The proposed methodology (depicted in Figure 1) will adopt a two-pronged approach. There will be **two** important components to this approach. The **first one** is the data capture and analysis on the enclosure which will be taken out to the roads and will capture images of the road surface and the corresponding road surface temperature using the onboard sensors. This is where all real-time data collection happens, which has been grouped under 'Real-Time Data' in the methodology chart shown in Figure 1. The enclosure would be mounted on the vehicle as shown in Figure 2(b). The road surface temperatures captured by the enclosure will then be validated by a thermistor/thermocouple (or any other contact type temperature sensor) housed on a local road. This same thermistor will also be used to validate the surface temperature relation developed by the machine learning model. The images captured by the onboard visible light camera will be analyzed by the image classification computer vision model deployed on board the microcontroller and will relay the real-time road surface conditions back to the base station via LoRa radio waves, which enable the onboard microcontroller to send and receive data from the base station.

All the electronic components used in the data acquisition will be housed inside the enclosure which has been made weatherproof. The road surface temperatures will be captured by the onboard IR sensors, MLX 90614 Infrared Thermometer, manufactured by Melexis. This sensor can detect temperature in the range of -20°C to 120°C, with a resolution of 0.02°C. The onboard camera used to capture images of the road surface is the Arducam Mini 2MP Plus which is a very popular IoT camera. It can also provide IR sensitivity with other mountable lenses. There is also a GPS module embedded in the enclosure, which can help keep track of the different routes traversed by the enclosure when aboard a vehicle. The GPS module used is the NEO-6M GPS module, which is very compatible with Arduino and other IoT components. All these components are connected to the SparkFun expLOraBLE Thing Plus microcontroller, which is especially useful as this has a highly integrated LoRa module which is especially useful for wireless data transfer to the base station. A simple sketch showing the enclosure and the components can be seen in Figure 2(a) below.

The **second one** will be the machine learning model which will have three important subparts parts and separate models in it. This is where all the predictive modelling happens, which has been grouped under ‘Predictive Data’ in the methodology chart shown in Figure 1. The first subpart will be a road surface temperature forecast model which will give out the road surface temperatures when the necessary weather parameters are given as an input. The second subpart is a surface condition prediction model which will give out the road surface condition (dry, wet, snow, ice, damp) when provided with the given input. The last and the third subpart is an ice prediction model which will supplement the surface conditions classification model by predicting if there will be ice on a particular road, with values ranging from 0-1, with 0 being no ice and 1 being possibility of ice.

This observed value of the road surface temperature can then be related to the road surface conditions and some other weather parameters using the surface condition model developed. That way the predicted road surface temperature coupled with other predicted weather parameters can be used to give a predicted condition of the road surface. For example, if the observed condition is <32°F and the relative humidity value is <= 60 then the condition of the road can be dry. This will be primarily done by the surface conditions prediction model and in some particular use cases, the ice prediction model.

The predicted road surface temperature can then be used by the local DOT to decide on the treatment that is to be made. The DOT uses a combination of pavement temperature nowcasting and estimated levels of precipitation dilution potential to determine application rates and types of salt [7]. The predicted road conditions and the predicted road temperature along with the real-time data can then go on a quickly updated dashboard which can be made available for public use. The dashboard will show the current and the forecasted road surface temperatures and road surface conditions at a variety of roads in the county traversed by the enclosure. The enclosure can be mounted on various types of vehicles, like TCAT buses, plough trucks, personal vehicles, etc. This will in effect give us a county-wide mobile road monitoring tool.

The measured road surface temperatures can also be added to the existing machine learning model in measured increments to update the weights of the model, ensuring that with each passing day the machine learning model can predict the temperatures better than the day before.

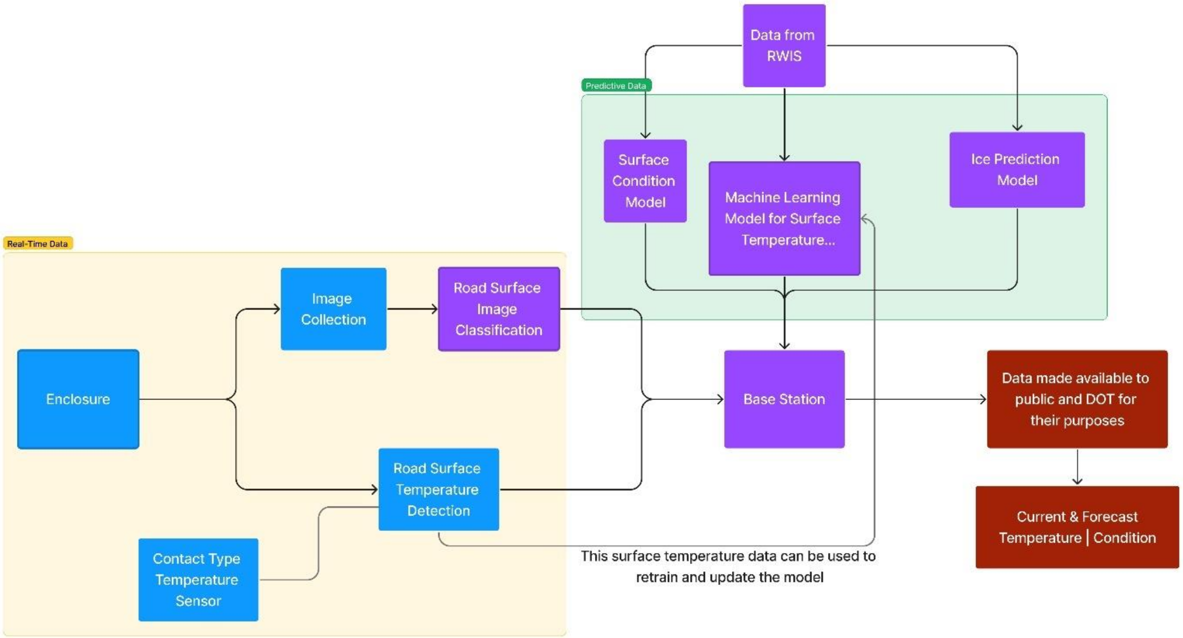


Figure 1. Proposed Methodology

(a)

(b)

Figure 2. (a) Enclosure with all its components labelled; 1 is the microcontroller with data acquisition components, 2 shows the battery pack, 3 is the GPS module, 4 is the

visible light camera, and 5 is the infrared camera. (b) The enclosure mounted on a vehicle

CHAPTER 3

MACHINE LEARNING MODEL FOR ROAD SURFACE CONDITION CLASSIFICATION AND PREDICTION

3.1 Introduction

Accurate prediction of winter road surfaces holds significant importance for local and state Departments of Transportation (DOT). It plays a crucial role in enhancing road safety by providing accurate information to drivers about hazardous conditions caused by snow, ice, and freezing temperatures. This information aids travelers in planning their trips effectively, choosing alternate routes if necessary, and preparing for potential delays or detours. Moreover, it guides DOTs in implementing appropriate road maintenance and treatment strategies more effectively, ensuring safer roadways. In emergencies, accurate road surface condition predictions can assist emergency services in navigating and responding efficiently. Additionally, it promotes public awareness and education about winter driving conditions, encouraging safe practices, and fostering a culture of responsible driving.

There are different methods by which DOTs determine the condition of the road surface at a particular time. Visual inspection and percussion for pavement inspection by winter maintenance crews are often adopted. Wireless sensor networks have also been employed to monitor large stretches of roads [2]–[4]. Road Weather Information Systems (RWIS) have been employed on long stretches of roads throughout the country, which provide vital information such as atmospheric, water level, and pavement conditions over several intervals throughout the day [1]. RWIS is a network of sensors that collect data on road weather conditions. This data can be used to improve safety and efficiency on the roads. RWIS typically collects data on air temperature, humidity, wind speed, and direction, precipitation type and amount, visibility, pavement temperature, and pavement condition [1]–[4].

Research on winter road surface condition (RSC) classification has followed a myriad of paths. Several works have been done on the use of sensors, such as near-infrared sensors, to detect road surface conditions [8]. Some other methods involved the use of detecting the change in friction to estimate the road condition [9]. Several experimental methods were also developed, such as detecting the road surface conditions by detecting the color differences (7) and using charged-coupled device (CCD) cameras to detect road conditions [10]. While experimental methods demonstrated valuable insights, it soon became evident that statistical methods, particularly those incorporating machine learning techniques, outperformed them in the detection and added another layer of predictive capabilities for detecting road conditions based on weather parameters.

There have been previous works on the detection of pavement surface conditions using machine learning (ML) algorithms, out of which tree-based algorithms such as random forest have been popular in recent years owing to the high levels of accuracy in their results. T Yu et al. [11] developed machine learning models, such as SVM, Multiple linear regression, Artificial Neural Networks (ANN), and Random Forest, to detect pavement surface index, out of which the random forest-based machine learning model obtained the highest R^2 value of 0.898. Takasaki Y et al. [12] developed a surface condition estimation method, based on random forest models that used road temperatures and traffic volume as the main parameters to estimate road surface conditions such as dry, wet, icy, and sherbet with an accuracy of 94.7%. There have also been several studies that used images to classify road surface conditions in winter [13]–[15]. Still, this technique has a few drawbacks, including the misclassification of images due to road salt present on the surface and harsh sunlight on the road surface. Most of these studies focus on real-time predictions, and none of them focus on future predictions (forecasts), which will be of significant use to employ accurate preventive methods, such as employing de-icing agents on road surfaces in time.

In this study, we bring light to a method utilizing machine learning techniques to explore and discover the relationships between weather parameters and real-time and forecasted road conditions. By leveraging advanced algorithms and analyzing large RWIS datasets, this approach can uncover intricate patterns and correlations, providing valuable insights for understanding how weather influences road conditions. We also introduce a method by which we add RSC forecasting capabilities to existing RWIS systems. This method has the potential to assist in proactive decision-making by the Department of Transportation by focusing on forecasts and help optimize road maintenance strategies, improve winter road surface classification accuracy, and enhance overall road safety.

To assess the effectiveness of the developed model, we conducted experiments by running it against forecasted weather values obtained from weather models. This evaluation allowed us to measure the model's predictive capabilities and determine its performance in capturing the relationship between forecasted weather parameters and road conditions in areas that are remote and do not have access to RWIS networks. By comparing the model's predictions with the actual road conditions observed during those forecasting periods, we gained insights into its accuracy, reliability, and potential for practical implementation, which will be discussed in this paper.

3.2 Methodology

3.2.1 Data

3.2.1.1 RWISds

We requested data from different RWIS stations located throughout New York State from June 2021 to May 2022 from the New York state DOT. However, only two RWIS locations, both located in Broome County, provided data of sufficient quality for use as this data was uniform and contained all necessary information without any significant gaps or missing values. The data from all other locations were either infrequent or incomplete due to sensor errors, with some locations having more than 60% of their data incomplete. The Broome County data, referred to as RWISds, had weather parameters such as ambient air temperature (°F), solar irradiation (W/m^2), relative humidity (%), wind speed (m/s), surface temperature at different depths (°F), dew point (°F), atmospheric air pressure (hPa), coefficient of road friction, saline concentration (lbs.p.l.mile), and water film height (mm) collected every 5 minutes.

The road surface conditions in the dataset were classified as follows; ‘dry’, ‘wet’, ‘snow’, and ‘ice’, the four main road surface conditions seen during winter months. The dataset contained one other surface condition, i.e., ‘damp’, which we re-classified as wet for our purpose due to the limited availability of ‘damp’ samples in the dataset. Additionally, when considering that the definition of ‘damp’ includes the characteristics of being ‘wet, and wet conditions are more significant in the context of winter road conditions, we decided to classify ‘damp’ samples as ‘wet’.

3.2.1.2 The HRRR weather model dataset

We also utilized data collected from the High-Resolution Rapid Refresh (HRRR) [16] weather model for all days from November 1, 2021, to March 31, 2022. The HRRR weather model is a short-term weather forecasting model developed by the National Oceanic and Atmospheric Administration (NOAA). The HRRR model is updated hourly with forecasts up to 48 hours ahead and has a high spatial resolution of 3 km. The high temporal and spatial resolution of the HRRR model can potentially enable us to forecast road surface conditions in real-time operations. The HRRR model also provides forecasts for a wide range of meteorological variables, including air temperature, relative humidity, wind speed, and direction, precipitation, cloud cover, and atmospheric pressure.

Since the accuracy of weather forecasts tend to decrease as the lead time increases, and forecasters tend to focus on shorter-term predictions for increased accuracy in predictions, we decided to focus on one-three-hour ahead forecasts for maximized accuracy. Added to this is the fact that road weather condition forecasts with better accuracy for shorter time intervals are more valuable because they allow for safer and more efficient travel, enable timely responses to weather events, and consider the high variability of local weather conditions. We believe that while longer-term forecasts remain important for planning and preparedness, emphasizing shorter-term accuracy is essential for addressing immediate safety and transportation needs.

3.2.2 Model Description

Figure 3 depicts the overall modeling approach. The RWISds will be used to develop the road surface condition model (referred to as "RSC Model" in Figure 1), which will predict the road surface conditions when given the input parameters such as ambient air temperature (°F), solar irradiation (W/m^2), relative humidity (%), wind speed (m/s), and water film height (mm). This will serve as the overarching model, on which the forecasted data from both the RWISds that we developed (which will be explained in the upcoming sections) and the HRRR weather data will be tested, to see how well our developed RSC model performs on each. This will give us an idea of how useful the RSC model will be in predicting real-world conditions, both real-time and forecast. The RWISds will be used to develop a regression model to predict the weather parameters for up to three hours into the future, which will then be used as the input to the RSC model. All these models and their performance metrics will be discussed in the subsequent sections.

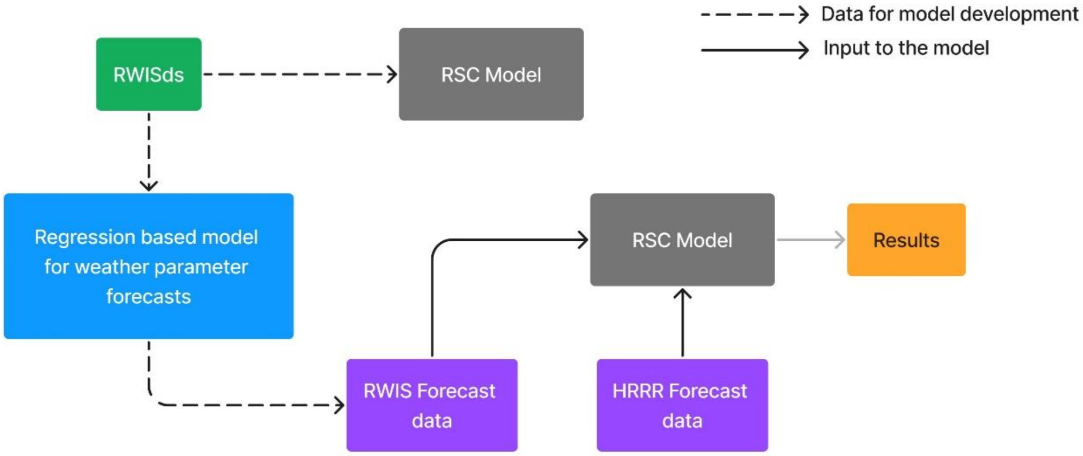


Figure 3. Methodology followed for developing and testing the RSC model

3.2.2.1 Road Surface Condition (RSC) Model

We developed the RSC model to predict road surface conditions such as dry, wet, icy, and snowy roads using different weather parameters as a classification problem. Several studies have found strong correlations between road surface conditions, road surface temperature, and ambient air temperature[17]–[19]. When we conducted a correlation analysis of the RWISds dataset, ambient air temperature (°F), solar irradiation (W/m^2), relative humidity (%), wind speed (m/s), and water film height (mm) have been shown to have high degrees of correlation with road surface temperature which in turn affects the road surface conditions. These were chosen as input parameters. The output of the model was taken as the road surface conditions detected by the sensors on the RWIS system in Broome County. The surface conditions of ‘dry’, ‘ice’, ‘snow’, and ‘wet’ were assigned the respective values of 0, 1, 2, and 3.

The dataset was split into a test-train split of 80%-20%, and an XGBoost classifier algorithm was trained on the dataset. eXtreme Gradient Boosting [20] is an ensemble learning algorithm in machine learning that combines many weaker models to develop a strong model. Gradient boosting is an iterative method that builds a model by adding new models that correct the errors made by previous models. XGBoost works by first creating a simple model, such as a decision tree. This model is then used to make predictions based on the training data. The errors made by this model are then used to train a new model. This process is repeated until the desired accuracy is achieved.

3.2.2.2 Regression models for weather parameter forecasts

We aimed to study the performance of our developed RSC model on short-term forecasts from the Broome County data, which contained historical data. This dataset laid the foundation for training and developing our short-term forecast model. We used the data collected from November 2021 till the end of March 2022 to develop the regression models because these months represented the winter months. We employed an XGBoost regressor algorithm, a machine learning algorithm widely used for regression tasks. After training the short-term forecast model, we used it to predict weather parameters for the next 3 hours based on past weather conditions. We then used the forecasted weather parameters obtained from the short-term forecast model as inputs to the RSC model. These inputs mimic real-world conditions and enable us to understand how well our developed RSC model performed on forecasted data from the RWIS.

3.2.2.3 Model Evaluation Metrics

To evaluate the forecasting capabilities of the developed RSC model, we conducted tests using forecasted data gathered from both RWIS and HRRR sources. The performance of the RSC model is assessed mainly through the confusion matrix, which presents a tabular representation of the model's predictions versus the actual class labels for individual classes. It provides valuable information on true positive, true negative, false positive, and false negative predictions, enabling us to assess how well the model distinguishes between different classes. In addition, we also report the accuracy score, which is an overall measure of the model's correctness in predicting the correct class labels.

3.3. Results and Discussion

3.3.1 Evaluation of the RSC model on observed RWIS data

The RSC model developed was first evaluated on its test set, which was set apart while preprocessing the data in test and train splits. The developed RSC model performs well on the test data, with a classification accuracy score of 100% on dry conditions, 98% on ice conditions and 98% on wet conditions. From the confusion matrix plotted below (Figure 4), which shows a comparison between the predicted classes and test classes, we see that the model performs well in classifying the real-time road surface conditions with an acceptable value accuracy when presented with the input parameters.

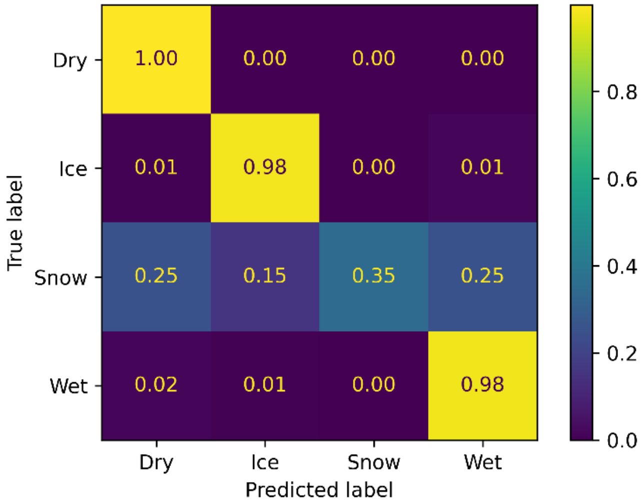
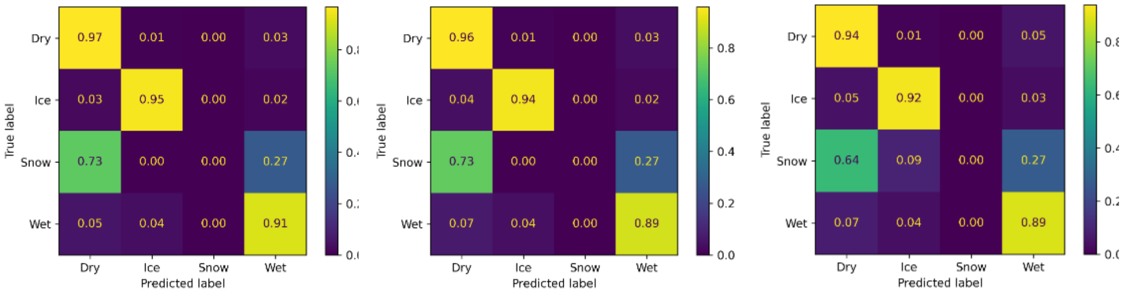


Figure 4. Confusion matrix showing the true value vs. predicted value of each class of road surface condition predicted by the RSC model on the real-time RWIS test set.

The confusion matrix shows that the model performs well in predicting the road surface conditions of icy and wet roads, which are widely considered to be the winter road conditions in which one should exercise most caution. From these results, we can gauge that the model can be particularly useful in addressing the challenges posed by black ice. Thus, we see that the RSC model developed offers valuable insights into the state of the road surface, considering factors such as air temperature, relative humidity, water film height, wind speed, and solar radiation.

3.3.2 Evaluation of the RSC model on RWIS forecast data

As mentioned in Section 3.2.2.2, we developed a localized forecast model using the RWIS data from Broome County using XGBoost-based regression to forecast the weather parameters such as ambient air temperature (°F), solar irradiation (W/m^2), relative humidity (%), wind speed (m/s), and water film height (mm) up to three hours into the future. With these forecasted weather parameters and corresponding road surface conditions, we tested the developed RSC model on this data. The confusion matrices showing the correct vs. incorrect predictions per class have been shown below (Figure 5).



(a) (b) (c)

Figure 5. Confusion matrices showing true labels vs. predicted labels of the regression-based RWIS forecasted data tested on the RSC model. (a) Shows the confusion matrix corresponding to 1 hour- ahead; (b) shows 2 hours-ahead and (c) shows 3 hours-ahead weather forecasts. These confusion matrices have been normalized to show the percentages of data represented in each tile.

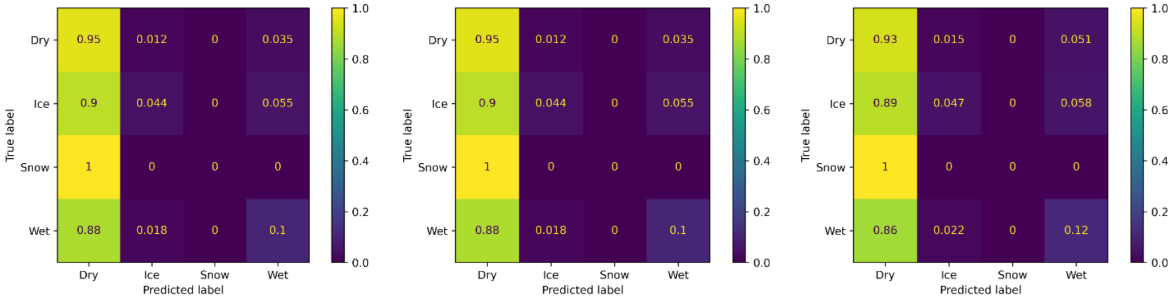
The confusion matrices in Figure 5 show the number of correctly identified classes by the model. We observe that the model demonstrates strong performance in identifying dry conditions, with an accuracy of 97.0%, 96.0%, and 94.0% for one hour ahead, two hours ahead and three hours ahead, respectively. It also exhibits relatively good accuracy in recognizing ice conditions at 95.0%, 94.0%, and 92.0%, followed by wet conditions at 91.0%, 89.0%, and 89.0% for one hour ahead, two hours ahead and three hours ahead. However, the model struggles with snow conditions, failing to correctly identify any instances in either of the confusion matrices shown above. This outcome can be attributed to the limited availability of snow samples in the dataset, with only 11 occurrences, leading to sparse data that challenges the model's accurate classification.

The road surface classification model shows promising capabilities for accurately identifying forecasted road conditions during the winter. The high accuracy achieved for ice and wet conditions is particularly valuable as these are prevalent and hazardous conditions that significantly impact road safety during colder months.

3.3.3 Evaluation of the RSC model on HRRR data

Evaluating the RSC model on forecasted weather model data would serve multiple crucial purposes. The primary and most significant advantage of our road surface classification model lies in its capability to be deployed effectively in regions lacking access to RWIS stations. This allows us to assess the model's real-world performance under evolving weather conditions, providing valuable insights into its ability to handle predictions in practical scenarios. Secondly, testing the model on forecasted data enables us to gauge its suitability for applications requiring immediate or near-future predictions, such as identifying the current road condition or chances of accumulation of ice on the road. Additionally, forecasted data often comes with inherent uncertainties and errors, and evaluating the model on such data helps us understand its robustness and adaptability to handle noisy inputs.

To do this, the road surface classification model developed was tested on the data collected from the HRRR [16] weather model for all days from November 1, 2021, till March 31, 2022, which particularly targeted the winter months. The data collected from the HRRR model included forecasts for one to three hours ahead. We observe that the model performs the best on the one hour ahead forecasts, showing decreasing values of accuracy with each hourly increment in the forecast values. The confusion matrix in Figure 6 shows the predicted versus true classification for each road condition for each hour of the HRRR dataset.



(a) (b) (c)

Figure 6. Confusion matrix showing true label vs. predicted label of the HRRR data used as input to the RSC model for (a) 1 hour-ahead, (b) 2 hours-ahead and (c) 3 hour-ahead weather forecasts. These confusion matrices have been normalized to show the percentages of data represented in each tile.

In Figure 6, we see that the HRRR forecast data does not work well with the RSC model developed, especially when it comes to icy, wet, and snowy conditions. Looking at the confusion matrices in Figure 6 we observe that the road conditions of ‘ice’, ‘wet’, and ‘snow’ have been incorrectly classified for most of the samples by the RSC model. The degradation in the model's performance can be attributed to the difference in the distribution of the weather parameters in the HRRR data and the data from the RWIS station, as shown in Figure 7. The correlation coefficients (r) between the different weather parameters in both the HRRR and RWISds were then calculated as 0.91, 0.69, 0.62, 0.58, and 0.25 for air temperature, relative humidity, wind speed, solar irradiation, and water film height respectively. This shows that water film height shows the weakest relationship between data recorded in the RWISds and HRRR data. The presence of significant errors in water film height forecasts should be the major contributing factor in the performance degradation. As the HRRR data reports precipitation rate instead of accumulated water film height on the ground, water film height forecasts are underestimated in this dataset.

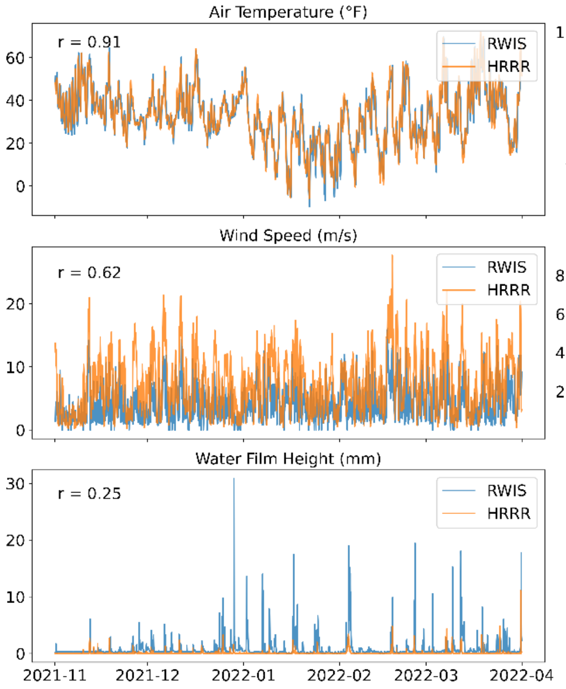


Figure 7. Data distribution comparison of different parameters between RWIS and HRRR model

This outcome is significant as it demonstrates that the regression-based approach, leveraging past data to predict weather parameters, outperforms the HRRR data indicating the importance of measurements at the site. One way to improve the RSC model's predictions would be to feed it with more accurate data from different locations. This way, the model will learn to make better predictions by understanding underlying patterns within the data. This can help generalize the model more and improve its robustness. Improvements in the weather models can also bring about better forecasts, which may lead to increased accuracy in the prediction of road conditions in the future.

In remote and rural locations, our road surface classification model has the potential to emerge as a crucial solution, offering accurate and timely insights into road conditions without the need for expensive and often unattainable RWIS infrastructure. This potential will be fully realized with meteorological advancement and as the weather models improve in the coming years. Consequently, implementing this approach along with the existing RWIS infrastructure could facilitate more effective decision-making and resource allocation for managing road conditions, leading to enhanced safety and operational efficiency.

3.4. Conclusion

Using the selected weather parameters such as air temperature, relative humidity, wind speed, solar irradiation, and water film height as features, we developed a road surface classification model using XGBoost classifier algorithm. We obtained a classification accuracy value of 98% on both ice and wet conditions on real-time RWIS data. A regression-based weather forecast model using the RWIS data was developed to assess the performance of the RSC classification model in predicting future, rather than real-time, road surface conditions. We obtained classification accuracies of up to 95% for ice conditions and 91% for wet conditions. The performance of the RSC model was also tested with up to three hour-ahead weather forecasts generated using the HRRR weather model. We found that our classification accuracies for ice and wet conditions deteriorated to 12% and 4.7% respectively, due to notable forecast errors in parameters such as water film height and wind speed in the HRRR weather model data when compared to the RWIS data.

To enhance the model's predictive capabilities, we firmly believe that further improvements are needed. One way we aim to do this in the future is by collecting additional data. By expanding the dataset to encompass diverse locations and multiple seasons, we seek to improve the model's generalizability and ensure its effectiveness in various scenarios. As shown in previous studies, this model can also be enhanced by adding other parameters, such as traffic volume. Collecting comprehensive and long-term observational data will play a crucial role in refining and advancing the model's capabilities. We also believe that as meteorological technology advances and weather models continuously improve, the potential for more precise forecasting will steadily grow. This evolution in weather forecasting will have far-reaching implications, including the ability to improve the RSC model’s predictive capabilities.

With the implementation of an enhanced and improved model, this solution holds significant potential, particularly in remote and underdeveloped areas where access to advanced facilities like RWIS is limited. In such locations, the road surface classification model can prove indispensable, providing precise and timely road condition insights without the necessity of costly and often unattainable RWIS infrastructure. This approach promises to bridge critical information gaps and contribute to a safer and more efficient winter commute in remote regions.

CHAPTER 4

MACHINE LEARNING MODELS FOR ROAD SURFACE TEMPERATURE PREDICTION

4.1 Introduction

The northern United States is no stranger to the bone-chilling embrace of winter. As the calendar turns to the winter months, the region is often enveloped in a frigid climate that brings snow, ice, and sub-zero temperatures. Navigating this treacherous environment requires more than just warm clothing; it necessitates a robust road maintenance strategy that considers fluctuating road surface temperatures (RST) to ensure safe and efficient travel for all. Well-maintained roads enhance safety, reduce accidents, and enable a swift response from emergency services. To achieve these goals, road maintenance crews employ a combination of strategies that are closely tied to road surface temperature monitoring. Proper prediction of RST is essential for deciding on the preventive measures such as applying anti-icing agents on roads, and scheduling plowing of the roads [7].

The prediction of asphalt temperatures sparked an interest in researchers as early as the mid-1900s. For ease of categorization, the stages of road surface temperature predictions can be categorized into three stages. In the first stage, from 1950 to 1990, researchers focused on using temperature distributions and trends to predict road surface temperatures. Some of them used slope methods to do the same. During the second stage, from 1990 to 2000, researchers focused on using regression models to predict road surface temperatures. In the third stage, from 2000-present, regression models based on statistical methods became the go-to for pavement temperature predictions. The vast improvements in the database have helped build better models as the years passed [21].

Analytical models using partial differential equations (PDEs) for heat conduction were developed, while alternative approaches like energy balance equations were also explored, and numerical methods such as finite element analysis (FEA) were utilized alongside techniques like finite element method (FEM), finite difference method (FDM), and finite volume method (FVM) [22]. These models rely on an abundance of field data on which these models are trained for predictions.

Barber [23] tried to address the internal asphalt temperatures using weather reports. This analytical model gave a maximum temperature error of 3-5°C, occasionally exceeding the 5°C mark. The LTTP (long-term pavement performance) project was developed by the United States in 1987, which compiled a database with parameters such as ambient temperature and solar irradiation and aimed to use these in a regression model that could be related to the pavement temperature [21].

Solaimanian and Kennedy [24] tried building a model which used ambient air temperature and solar irradiation account to predict the maximum road surface temperature. It did not, however, take the winter conditions into account and gave a maximum road surface temperature value within 3°C, 85% of the time. Park et al. [25]

developed a relationship between the surface temperature at different depths with surface temperature, depth, and coefficient of time. This model was verified for temperatures ranging from -28°C to 54°C. Matic et al. [26] developed a linear model to detect surface temperatures by equation of air temperature and depth in Serbia.

Regression based machine learning models have also been put into use quite a lot when it comes to asphalt temperature predictions. Khan Z.H. et al. [27] developed regression models to predict asphalt surface temperatures in New Mexico, USA. They developed daytime, nighttime, and 24 hours models out of which the 24-hour model performed best with a R^2 value of 0.974 and RMSE of 4.11°F. This was validated on a completely new dataset from the same location which yielded an RMSE value of 5.73°F showing the reliability of the model.

There have been several studies on the use of neural networks to predict road surface temperatures. T. Ghalandari et al. [28] used several machine learning algorithms such as autoencoder network, Feedforward Neural Network (FFNN) and Long Short-Term Memory (LSTM) to develop asphalt temperature prediction models out of which the autoencoder network worked best. They then compared the accuracy of the developed machine learning model to a validated Finite Element model and found that the machine learning model predicted asphalt surface temperatures more accurately than the finite element model.

A flexible pavement's response to varying loads is predicted mathematically using the BELLS model. The BELLS model was developed by the Federal Highway Administration (FHWA) based on the LTPP Seasonal Monitoring initiative, which utilizes the mean air temperature from the previous day to account for weather-related fluctuations and minimize errors [29]. The physical characteristics of the pavement materials, the loading circumstances, and environmental variables that may have an impact on the performance of the pavement are all considered by the model. The model is used to design flexible pavements, which are often comprised of asphalt or other bituminous materials, and to assess their performance. The extensions of the BELLS model, BELLS2 and BELLS3 are used to determine the asphalt pavement temperatures using the LTTP Protocol and routine testing methods [30].

The rest of the chapter is organized as follows. The next section discusses the available data used in this study and the description and methodology employed in creating the RST prediction models. The results and discussion will follow this section in which we will test our models developed on the testing data.

4.2 Methodology

4.2.1 Data

4.2.1.1 RWISds

We requested data from different RWIS stations located throughout the state of New York from the NY state Department of Transportation (NYSDOT) from June 2021-May 2022. These data contained several weather variables like air temperature (°F), wind speed (mph), relative humidity (%), etc. along with other surface variables such as ice percentage (%), water film height (mm), surface, and sub-surface temperatures (°F). Only two locations situated in Broome County provided data of sufficient quality for use as all other locations had incomplete data, ranging up to 60% of incompleteness in data in certain locations. This dataset is named RWISds, where ‘ds’ stands for dataset.

4.2.1.2 GFRds

We collected a testing dataset, by coupling the road surface temperatures collected in the Game Farm Road in Ithaca with the weather stations situated on that road. From 16th of March till 29th of March, the road surface temperatures (°F) at Game Farm Road (GFR) in Ithaca (Figure 11) were measured using a contact type temperature sensor. The road surface temperatures collected by the contact type temperature sensor were verified using hand-held industrial grade IR temperature guns. The location of the contact type temperature sensor has been outlined in red in the map below (Figure 8). The road surface temperatures recorded from this site were coupled with other weather variables such as air temperature (°F), wind speed (mph), relative humidity (%) and solar irradiation (W/m^2) from the adjacent weather station on the same road.

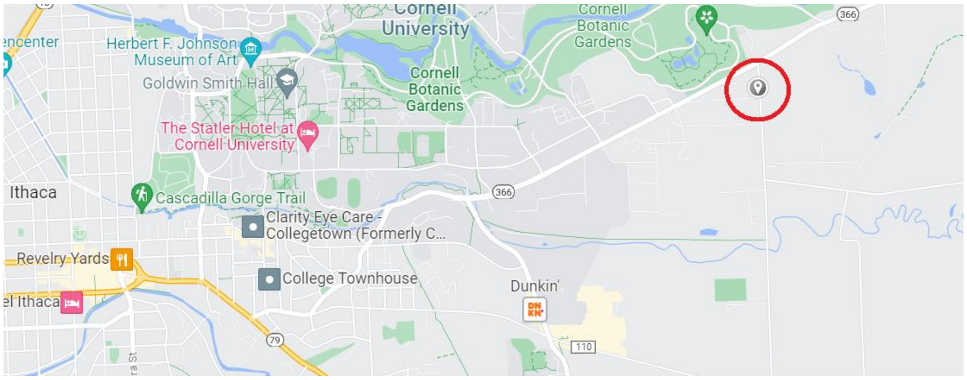


Figure 8. Map showing the location of the Game Farm Road site [31]

4.2.1.3. Enclosureds

To test the model(s) developed using the GFRds, we collected RST data using our low-cost IoT enclosure which had an infra-red temperature sensor embedded in it. The enclosure was driven around Ithaca and the data was collected over a period of 6 different days spread throughout the months of March, April, and May of 2023. The enclosure collected data for a period of roughly one hour each day, and the IR temperature sensor had its emissivity value set to 0.9, to align with the most common emissivity values of asphalt.

4.2.2 Model Description

For developing a road surface temperature predictive model, we would need to establish the relationship between road surface temperature and other weather parameters. For this, Spearman's rank correlation is used, which gives out a measure of the strength of association between two given variables [32]. The data used to determine Spearman's rank correlation was taken from the months of December-March, 2021-2022 from RWISds. These months were chosen because they represent the winter conditions best. The heatmap (Figure 8) shows the correlation between different weather parameters and the road surface temperature that showed good correlations. The highest correlation is between the ambient air temperature and road surface temperature, followed by solar irradiation (GHI), average wind speed, and relative humidity (RH).

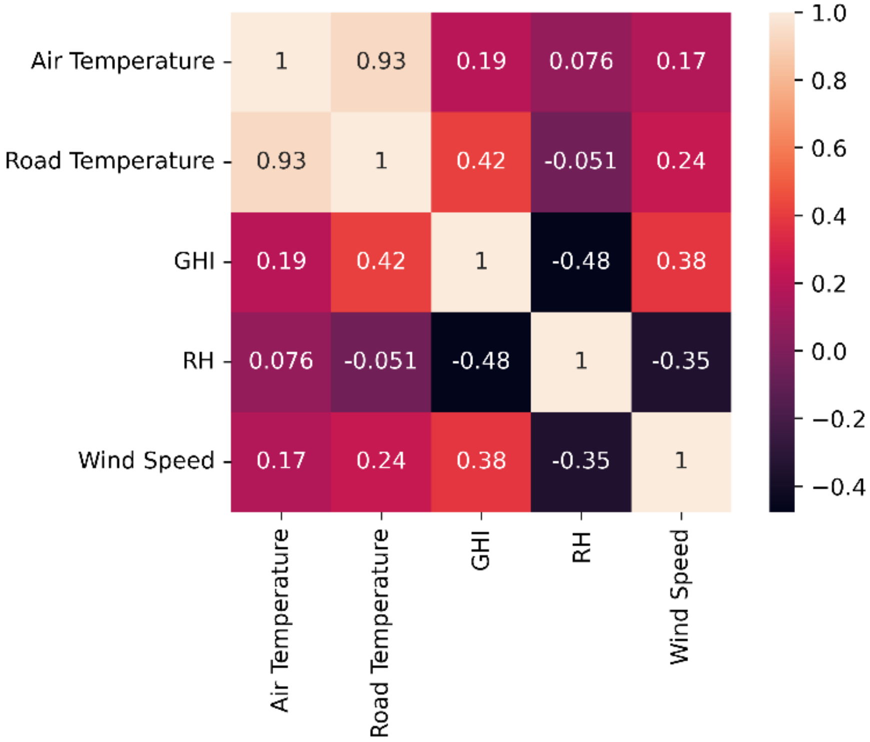


Figure 9. Heatmap showing the correlation between various weather parameters and the road surface temperature

The data collected from RWISds was analyzed using both an eXtreme Gradient Boosting (XGBoost) algorithm [20] and a Random Forest [33] algorithm (RF) which are considered powerful machine learning algorithms, as it combines many weaker models to come up with a strong model. Gradient boosting is an iterative method that builds a model by adding new models that correct the errors made by previous models.

XGBoost and Random Forest work by first creating a simple model, such as a decision tree. This model is then used to make predictions based on the training data. The errors made by this model are then used to train a new model. This process is repeated until the desired accuracy is achieved.

These models (XGB and RF) are ensemble techniques made up of many different decision trees. Each tree produces its own forecasts, and the combined projections of all the trees yield the final prediction. As a result, these models' decision boundaries are not linear and cannot be described by a simple equation with slope and intercept. Hence, no straightforward equation exists for an XGBoost model, or an RF model developed.

The data from RWISds was used to develop a XGBoost regressor model (BroomeXGB) and RF regressor model (BroomeRF). The months from December to March (2021-22) were used to develop the model. The pavement temperature at the surface depth was made the dependent variable, and the ambient air temperature, solar irradiance, average wind speed and relative humidity were all considered as independent variables based on the correlation analysis. The data was split into a test-train split of 80%-20%.

The performance of boosting models such as XGBoost or bagging models such as Random Forest can be better optimized by performing hyperparameter tuning. Both algorithms offer several hyperparameters that can be tuned to improve model accuracy and generalization. However, the process of hyperparameter tuning often involves some trial and error to find the best combination of values. The learning rate, number of trees, maximum depth of each tree, subsample ratio of training instances, L1 and L2 regularization values, are some of the hyperparameters that were tuned by the method of trial and error to yield the results which will be discussed in the next section.

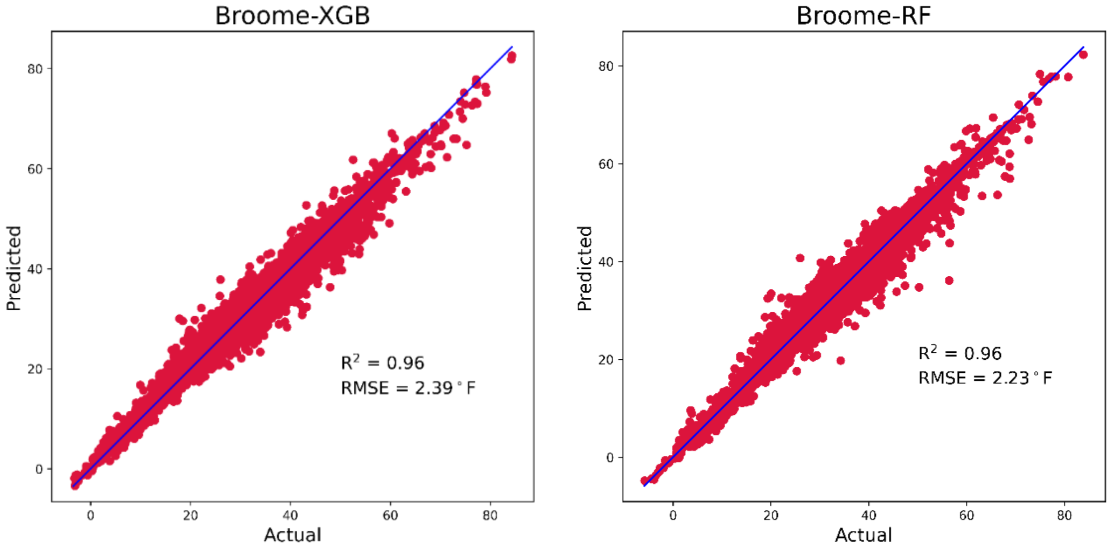
4.2.3 Model Evaluation Metrics

The performance of the RST model is assessed mainly using two parameters, the R^2 (coefficient of determination) which is a value shows the goodness of the fit of a model and the root mean squared error (RMSE) which measures how far, on an average, the predicted values are from the true values. The R^2 score can help assess how well the model fits the data and the RMSE value can supplement this by indicating how accurate the model's predictions are. Ideally, we would want high R^2 and a low RMSE values to represent a good performance of the model.

4.3. Results and Discussion

4.3.1. Evaluation of Broome-XGB and Broome-RF on RWISds

The model (Broome-XGB) developed using XGBoost yielded the following metrics: $R^2 = 0.96$ and the RMSE = 2.39°F, which is significantly better than the regression model. The Random Forest model (Broome-RF) yielded the following metrics: $R^2 = 0.96$ and the RMSE = 2.23°F, which is as good or slightly better than the Broome-XGB. The comparison between the actual and predicted temperature values using the XGBoost algorithm, and Random Forest (RF) algorithm is shown in Figure 9.



(a) (b)

Figure 10. Comparison between RST and Predicted RST in the (a) XGBoost model on the Broome County dataset, and (b) RF model on the Broome County dataset

4.3.2. Evaluation on GFRds

We then used the GFRds data to test the Broome-RF model developed. The performance metrics have been tabulated in Table 1 and the comparison between the predicted and the observed temperatures have been shown in Figure 10. The performance metrics obtained prove that the data collected by the sensor is good enough to be used to develop machine learning models which have the potential to work well within Tompkins County.

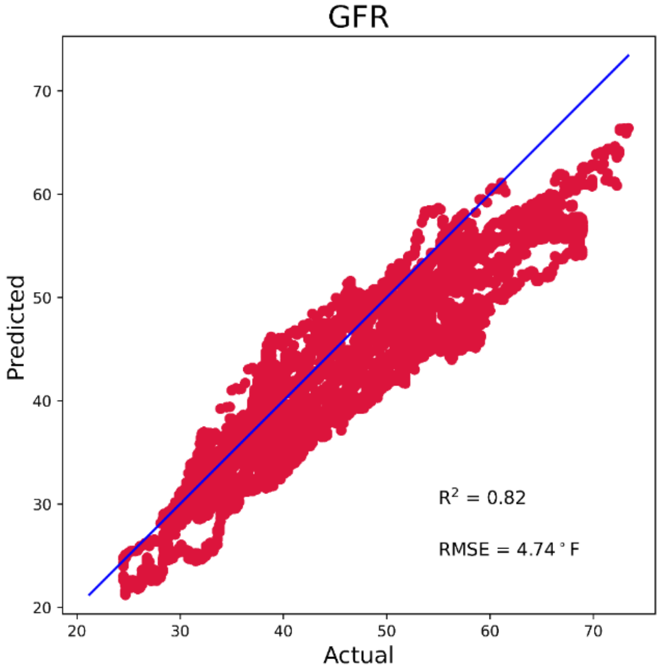


Figure 11. Comparison between test RST and predicted RST in the Game Farm Road (GFR) dataset using the Broome-RF model developed

Table 1. Performance metrics of Broome-RF model developed on its test set and the GFRds

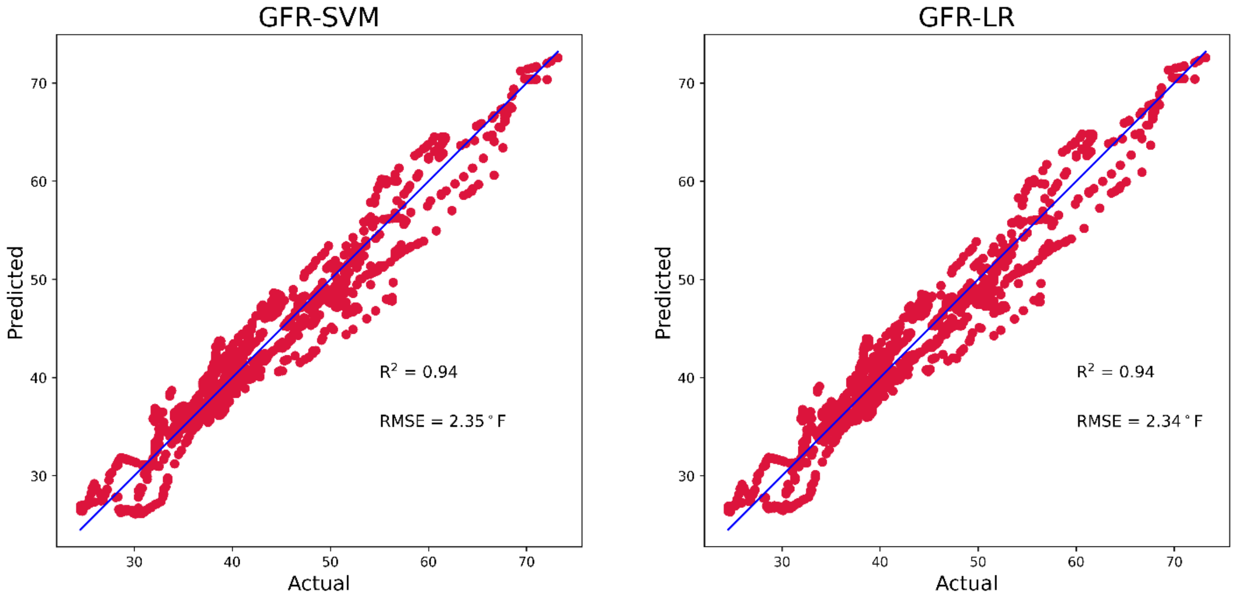
Location	**R^2**	**RMSE (°F)**
Broome County	0.96	2.23
Game Farm Road	0.82	4.74

Thus, four different kinds of machine learning models were developed on GFRds and the best model out of these was chosen. The data was split into an 80-20 train-test split and the four models developed were Linear Regression, Support Vector Machines

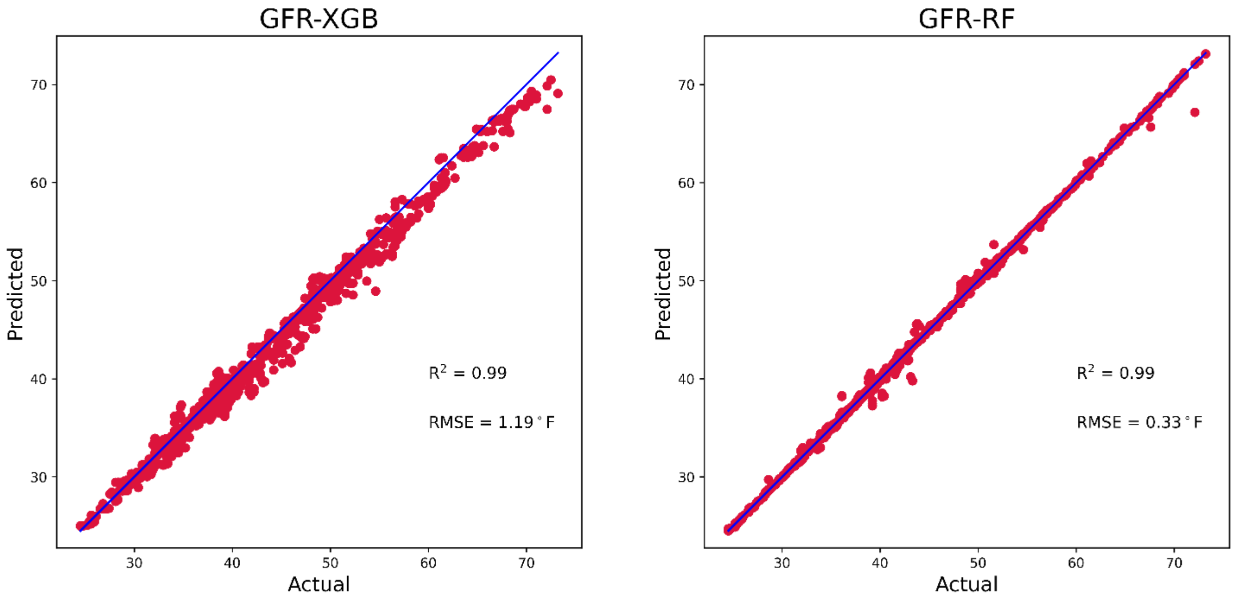
(SVM) [34], XGBoost and Random Forest. The performance metrics obtained by all four models have been tabulated in Table below. The figure (Figure 12) shows the comparison between test RST and predicted RST in the Game Farm Road dataset using the different models developed. The performance metrics for each of these four models developed have been tabulated in Table 2.

Table 2. Performance metrics of the different models developed on the GFR dataset

Model	**R^2**	**RMSE (°F)**
Linear Regression	0.94	2.35
SVM	0.94	2.34
XGBoost	0.99	1.19
Random Forest	0.99	0.33



(a) (b)



(c) (d)

Figure 12. Comparison between actual RST and the predicted RST on the models developed on the GFR dataset. (a) shows the comparison and the SVM model metrics, (b) shows the Linear regression, (c) shows the XGBoost, and (d) shows the Random Forest. It is seen that the Random Forest model performs the best with the highest R^2 and the least RMSE value.

It is clear in the comparisons that the Random Forest model performs the best, followed closely by the XGBoost model, and these two models will be used in all evaluations from this point.

4.3.3. Evaluation of GFR-RF and GFR-XGB on Enclosureds

The Random Forest model developed on the GFR data (GFR-RF model) and the XGBoost model developed on the GFR data (GFR-XGB) was then used to evaluate the performance of the road surface temperatures collected by infrared (IR) sensor mounted on the enclosure (Enclosureds), which have been collected and unified with corresponding weather station data on the GFRds.

A sample of the table showing the comparisons between the road surface temperatures predicted by the GFR-RF model and the GFR-XGB model, the contact type temperature sensor on GFR, and the IR sensor on the enclosure have been tabulated below (Table 3). Three different locations were chosen in Ithaca, the Game Farm Road (GFR), Cornell Orchards (Orchards) and Ithaca Airport (Airport) mostly because of the presence of RWIS stations in those locations. The Orchards and the Airport had no contact type temperature sensor on their roads.

Table 3. Table showing comparisons between the road surface temperatures predicted by the machine learning models and detected by the sensors at three different locations in Ithaca on two different days.

Date	**Time**	**Location**	**ML Model (°F)**		**Contact Type Temperature Sensor (°F)**	**IR Sensor (°F)**
			GFR-RF	**GFR-XGB**		
28th	22:00-	GFR	38.1	37.9	36.8	40.6

March 2023	23:00					
28th March 2023	22:00-23:00	Orchards	39.9	36.7	-	40.8
28th March 2023	22:00-23:00	Airport	36.3	35.2	-	42.7

3rd May 2023	16:30-17:30	GFR	62.7	57.2	59.4	58.6
3rd May 2023	16:30-17:30	Orchards	65.5	59.04	-	62.6
3rd May 2023	16:30-17:30	Airport	57.7	54.6	-	59.5

The figure (Figure 13) shown below shows the comparison of the road surface temperatures predicted by the machine learning models (GFR-RF and GFR-XGB), with respect to the true temperature that was collected by the IR sensor, on all the days the data was collected. From the plot we can observe that the GFR-RFR model performs better than the GFR-XGB model, with an R^2 value of 0.91 and RMSE of 2.86°F when compared to the R^2 value of 0.83 and RMSE of 3.43°F of the RFR-XGB model. We can also observe that both the models show an acceptable performance in predicting the road surface temperature values.

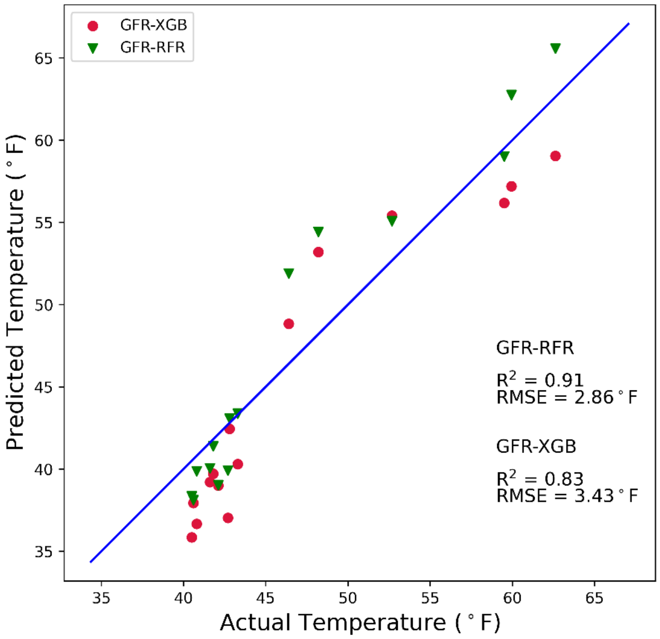


Figure 13. Evaluation of the GFR-RFR and the GFR-XGB models on the data collected by the IR sensor mounted on the enclosure. We can observe that both the models show an acceptable performance in predicting the road surface temperature values.

4.4 Conclusion

The result of these studies is promising and suggest that machine learning models can be used to effectively predict RST which can help improve road safety during winter months. A few limitations of this study should also be considered, such as uncertainty of generalization as this study was focused on Tompkins County in a specific time period. One of the main limitations of this this study is the limited dataset. The data collected was only for a period of 6 days and the lowest temperature recorded was 28°F. To make up for this limitation, we can utilize the Broome-XGB or the Broome-RF models developed to complement the GFR-RF/XGB model when the temperature drops below 28°F.

Despite these limitations, the results of this study provide a very valuable starting point for future research on the use of machine learning to predict RST locally. This study demonstrates that low-cost IoT devices can be used to create a road surface condition monitoring tool that can provide rural and remote communities with a taste of the power of RWIS systems.

CHAPTER 5

IMAGE CLASSIFICATION MODEL FOR ROAD SURFACE CONDITION CLASSIFICATION

5.1 Introduction

Computer vision is a branch of artificial intelligence that deals with enabling computers to interpret, analyze and understand visual data, such as images and videos, like human beings. The goal of computer vision is to mimic the human ability to perceive, understand and interpret the visual world to extract useful information from their surroundings. There are various tasks that can be done with computer vision which include but are not limited to image classification, object detection, segmentation, reconstruction, etc. In this chapter, image classification will be the primary focus. We will also be discussing a novel method of detecting temperature from road images in chapter 6.

Image recognition techniques have been extensively employed in detecting road surface conditions in places that experience severe winter conditions. Image classification, a prominent area of research in recent years, plays a crucial role in computer vision and serves as the foundation for various visual recognition applications [35]–[40]. Amongst the machine learning models proposed, CNNs (Convolutional Neural Networks) are the most sought after to perform pattern recognition problems. A CNN is a deep learning algorithm which can help differentiate different features in images. CNNs, to create a more abstract representation of the input image, a series of filters are used to identify features in the input image. Up until the network can recognize the required pattern, this procedure is repeated multiple times, with the filters being increasingly more abstract [41]. By avoiding manual feature engineering, a CNN may automatically figure out which features are most crucial for a certain task.

Pan et. Al [13] evaluated the ability of a pre-trained residual-CNN model to predict the road surface conditions in winter months using four of the most successful CNN models available, VGG16, Resnet50, Inception-V3 and Xception. They found that the Resnet50 gave out the most accurate predictions with the lowest variance with an accuracy value ranging from over 90% for all four models for multi-class classifications. C. Zhang et al. [14] developed a computer vision model that used images from both visible light cameras and thermal light cameras to classify winter road conditions into icy, snowy, slushy, or wet. The CNN model they developed achieved a weighted average F1-score of 94.0% on their base test set and F-1 weighted average score of 90.6% on a different test set. Nolte et al. [15] conducted a study evaluating the performance of CNNs in classifying road conditions categorized into asphalt, wet asphalt, dirt, grass, cobblestone, and snow. The dataset used in this study was collected from existing publicly available road images data. The study used two models, InceptionV3 and ResNet50, out of which both these models had a classification accuracy of about 90% with the ResNet50 being slightly better by 2%.

In this study, we will make use of transfer learning using the YOLOv5 [42] image classification architecture to train road surface images of different conditions observed in winter such as ice, snow, slush, wet and dry conditions.

5.2 Methodology

Image classification entails categorizing or labeling a whole image depending on its contents. Here, the images captured of the road surface (Figure 14) will be classified into five main classes: dry, wet, snow, ice, and slush. We make use of transfer learning by training our images on the YOLOv5 model and classifying them into different classes.

5.2.1 Dataset Description

The computer vision model aims to classify the road surface images into five main categories- dry, wet, snow, ice, and slush. The images captured by the sensor onboard were of dimensions 320 x 240 pixels. Some sample pictures in the dataset have been shown in Figure 14. The computer vision model was supplemented with images from two other datasets- one being a large-scale road surface conditions image dataset collected in Beijing, China from October 2021to May 2022, with images belonging to 27 different classes and of the size 240 x 360 pixels [43]. This dataset can be called Beijingds for ease of use. The other from RoadSaW which is a large-scale dataset for road surface and wetness level estimation collected in Hanover, Germany in 2021 [44]. This dataset had images corresponding to wet and dry conditions on three different surface types-concrete, asphalt, and cobblestone. This data was recorded on 10 different days using cameras mounted on vehicles.

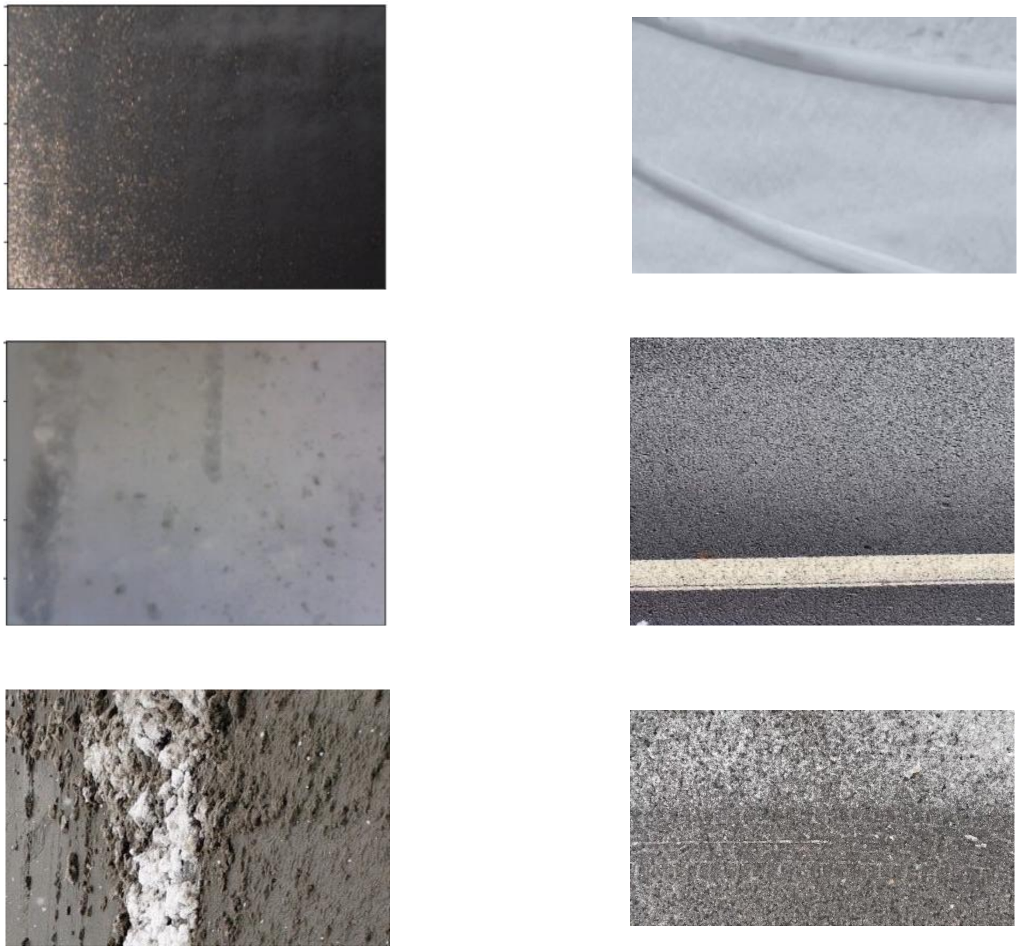


Figure 14. Sample images of the road surface used for training the classification model.

The classification computer vision model used images from existing datasets because different datasets often contain images captured under different conditions, from various sources, and featuring diverse subjects. By combining multiple datasets, the model is exposed to a broader range of visual variations, which can enhance its ability to generalize and perform well in a wider array of real-world scenarios. This would also help reduce the bias and improve the robustness of the model.

5.2.2 Model Description

YOLO ("You Only Look Once") is a popular real time object detection and classification software for computer vision tasks. The quickness and effectiveness of YOLO is one of its key advantages. YOLO conducts both object proposal and classification in a single forward run of the network, making it substantially faster than many existing object detection systems that use two-stage methodologies (for example, region proposal followed by classification). In YOLOv5 classification, features are extracted from input photos using a deep convolutional neural network, like one trained on ImageNet [45], and then mapped to corresponding object labels using a SoftMax activation function. The network is trained using a binary cross entropy loss function that penalizes incorrect predictions and encourages the network to make accurate predictions [46].

The computer vision model was annotated on Roboflow [47] and split into five classes namely, wet, dry, ice, snow, and slush. The dataset generated comprised ~19000 images split into a train-test-validation split of 70-20-10 percentages. Several image augmentations such as flip, horizontal, crop, rotation, and shear were used to further enhance the original dataset. A special type of augmentation called cut-out (black square boxes) was used on the training images to simulate the dust/dirt splatter on the camera when it is out in roads especially in slushy or wet conditions. Figure 11 shows a few images with all the augmentations from the train set which were supplemented with images from the Beijingds and RoadSaW datasets. This annotated dataset was then trained on the YOLOv5 model [42] with 149 layers and over 1.2 million parameters for a total of 90 epochs on a Google Collab notebook which utilizes the NVIDIA Tesla P100 GPU aaccelerator.

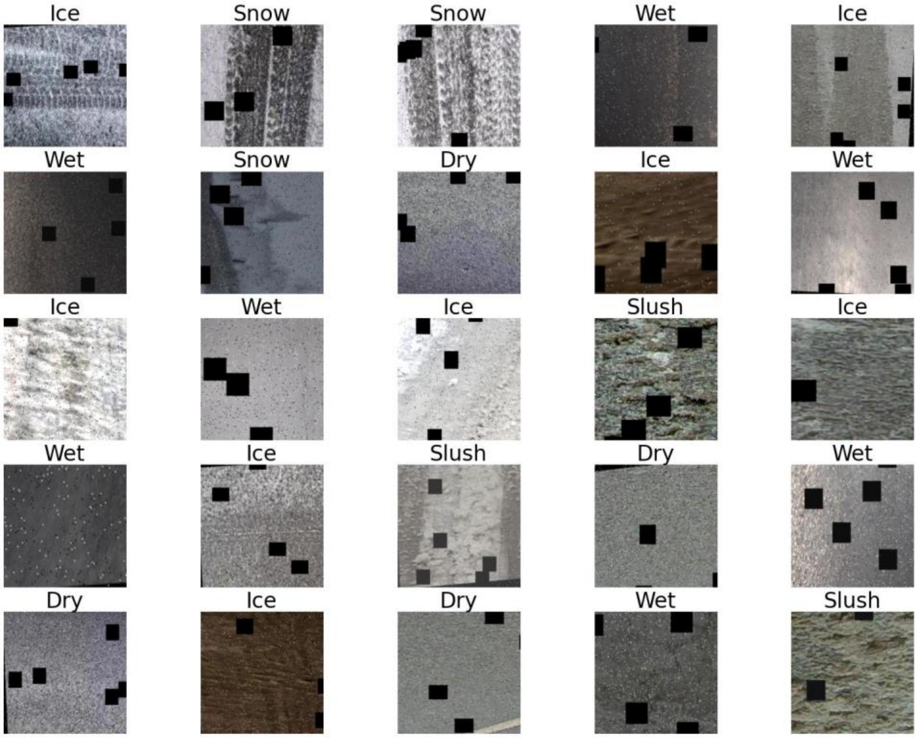


Figure 15. Train set images with augmentations added.

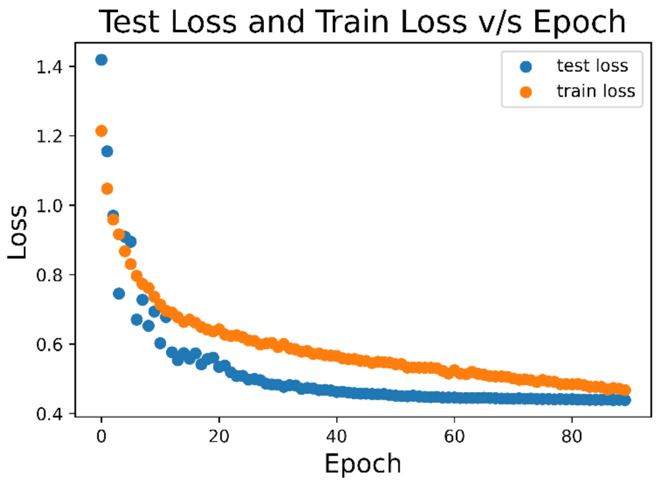


Figure 16. Test and Train loss with respect to the number of epochs.

5.3 Results and Discussion

The training accuracy obtained was 98.1% and the testing accuracy obtained was 96%. The train-test loss vs the number of epochs has been shown in Figure 16. We see that both the losses stabilize around a value of 0.45 at the 82nd epoch. The table below (Table 4) shows the overall accuracy of the model, which shows how accurately the model can correctly predict an image, and the accuracy values obtained per class. It is seen that the model performs well but has some trouble has some trouble when it comes to differentiating between ice, snow, and slush road conditions. This can be seen while analyzing the confusion matrix developed on the test set in Figure 18. Figure 17 shows a few figures with all the class prediction probabilities listed in the top left corner.

Table 4. Test accuracies corresponding to each class.

Class	**Accuracy**
Overall	0.98
Dry	0.98
Wet	0.99
Snow	0.98
Ice	0.97
Slush	0.99

Figure 17. Examples of test images with the probabilities of all classes.

From the confusion matrix in Figure 18, we see that the model correctly identifies images from all 5 different classes to an acceptable level of accuracy. The model struggles with classifying ice conditions, as they are often confused with slush and snow conditions. The slush conditions are also seen to be incorrectly classified as ice conditions on few occasions. This observation underscores the inherent difficulty in distinguishing between these visually similar categories, which may share common visual cues such as reflective surfaces or varying degrees of white texture. Further refinement in the training process could potentially address this specific challenge and improve the model's ability to differentiate between these closely related classes.

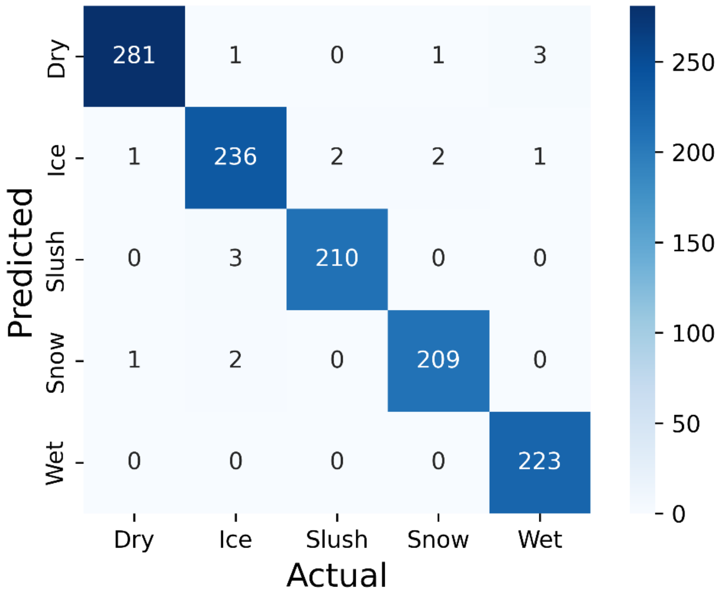


Figure 18. The Confusion Matrix developed on the test data showing the number of correctly classified images in the diagonal corresponding to each class.

5.4 Conclusion

In conclusion, the trained model exhibits strong overall performance, achieving high classification accuracy of 98% on the test set. However, it faces some difficulties in accurately classifying certain image categories, specifically in distinguishing between different road conditions involving ice, snow, and slush. Further improvements or modifications to the model architecture, additional training data specifically targeting these challenging classes, or feature engineering may help enhance the model's performance in these problematic areas.

The developed model for classifying road surfaces in winter conditions has the potential to greatly enhance safety and convenience for people. By accurately identifying different road conditions, such as dry, wet, icy, snowy, or slushy, the model enables individuals to make informed decisions while traveling. It facilitates road condition awareness, allowing drivers and pedestrians to adjust their behavior and choose appropriate routes. Integration into navigation systems and weather applications enables precise route planning based on real-time road conditions. Additionally, local authorities can utilize the model's predictions to prioritize road maintenance efforts, ensuring safer driving conditions. We believe the model's classification capabilities can also be integrated into public safety alert systems, issuing timely warnings and advisories to further enhance road safety during the winter months.

CHAPTER 6

COMPUTER VISION MODEL FOR DETECTING TEMPERATURES FROM IMAGES

6.1 Introduction

Winter road maintenance is crucial as it improves the safety, accessibility, and economic well-being of communities during the challenging winter months. Regular maintenance measures, including snow plowing, salting, and sanding, play a crucial role in mitigating the effects of winter weather on road conditions, guaranteeing smoother and safer travel in the winter months. A road weather information system (RWIS) is a network of sensors that are mounted on the road sections of interest, that collect data on road and weather conditions. These systems typically collect data such as ambient air temperature, humidity, wind speed and direction, solar irradiation, precipitation type and amount, and pavement temperature [1]–[3]. The evaluation of data from these sensors helps officials determine the best course of action for winter road treatments.

The detection of road surface temperatures is particularly important as they are one of the three main factors, along with chemical dilution and traffic volume, that influence the design of snow and ice treatment methods, as they especially affect an ice control chemical’s effectiveness and longevity as described by Amsler [7]. The speed at which an ice control chemical melts ice, as well as the quantity of ice it can melt, are both influenced by the road surface temperature. When the surface temperature drops, the ice control chemicals' ability to melt ice decreases, which also slows down their melting rate.

Road surface temperature detection and prediction are predominantly done by employing either numerical methods or statistical methods. The numerical methods [23], [48], [49] would employ analytical models using partial differential equations for heat conduction to estimate road surface temperatures. In the later years, statistical methods using regression-based models became widely used [24]–[26]. The most common statistical method to use was linear regression which map linear relations between several weather parameters and the target parameter, road surface temperature [50], [51]. This shift was primarily powered by the increase in computational power and introduction of machine learning methods. Insufficient data availability, leading to low accuracy in numerical methods, also played a role in driving the transition towards statistical methods [52], [53]. Later, employing more powerful machine learning algorithms such as gradient boosting improved the accuracy by a significant margin from simple linear regression-based models [52], [54]. These statistical approaches operated based on data, and more recently, the availability of RWIS has proven valuable in furnishing this data.

The RWIS sensors employed on the roads are often susceptible to weather damage, especially the road surface sensors when placed in the path of snowplows [55]. Even though the life span information of an entire RWIS system can vary from 10-20 years

[2], it can also be rendered temporarily out of commission by adverse weather conditions at a particular place at any point in time. When the sensors that measure surface temperatures, and conditions go offline, it detrimentally affects winter road maintenance because the maintenance managers have less data with which to decide on the proper treatment.

To negate this, an alternate system of surface temperature measurement is proposed by training neural networks on road images collected from road CCTV cameras in this study. The studies that served as inspiration for this work have been listed in this paragraph. Zheng et al describe work on finding out the human body temperature using just the facial images [56] using convolutional neural networks (CNNs) to extract facial features and a support vector machine (SVM) classifier to predict the temperature range. Other related work includes human age prediction using CNNs [57]–[59]. These methods have been effective with accuracy ranging anywhere from 55% to 85%. This technique can be used and modified in such a way that the CNNs can be used for regression to predict specific temperature values for specific images.

This work introduces a novel computer vision model specifically designed to detect road temperatures from CCTV images. This approach harnesses the power of machine learning and image analysis to directly infer road temperatures, presenting a new and efficient solution in the field. This model (TimgsNET) can be an alternate road surface temperature estimator when the pavement sensors fail or when such sensors are unavailable. By integrating TimgsNET as a secondary system within RWIS, its adaptability and potential for widespread adoption are demonstrated. This synergy capitalizes on existing camera infrastructure, offering a cost-effective means of enhancing the capabilities by utilizing images from CCTV cameras of RWIS without necessitating extensive additional hardware or infrastructure investments. This advancement also holds the promise of positively impacting life in rural and remote communities, which often lack the availability of RWIS infrastructure along their roads.

6.2 Methodology

This first step is to obtain and parse a well-documented dataset as described in Section 6.2.1. Subsequently, a CNN architecture is employed for training the model as discussed in detail in Section 6.2.2. The work explored various commonly used loss functions and will outline the computational hardware utilized in the process. Finally, this section will be concluded by describing the performance evaluation parameters used in this study.

6.2.1 Dataset Description

The data used in this section was collected from a dataset of road CCTV images and weather data collected by the Polish General Directorate of National Roads and Motorways from a period of November 2018 to March 2019 [60]. From this data, 153,200 data points are extracted for this study. This dataset (POLds for short) contained detailed information on the weather conditions, such as air temperature at 2m (°C), relative humidity (%), dew point (°C), wind speed (m/s), wind direction, and road surface conditions (dry, wet, moist, snow and ice) and temperatures at 0cm and 5cm depths (°C), along with the associated CCTV images during this period. Figure 19 shows a few images from the dataset.

To focus the analysis on a relevant temperature range that portray winter roads, the dataset was preprocessed such that only the images captured within the -20°C to 10°C road surface temperature range were extracted. This temperature range is of particular interest as it represents the temperatures most seen in the winter months, which is the primary focus of this study. A smaller temperature range, from -12°C to 0°C is also focused on in this study for post-analysis as this range is important in determining the apt de-icing strategy to employ [7].

Figure 19. Sample images from the dataset

The dataset used had approximately 153,200 images (dataset D1) and corresponding temperatures after preprocessing. The dataset D1 was split into two parts for training and evaluation. Set T1, with 10 percent of the data, was set apart for evaluation after developing the model. The remaining 90 percent (Set D2) was split into a test-train-validation split of 20%-70%-10% respectively. The dataset D1 was randomly shuffled before any of the splits were done. Figure 20 shows this splitting graphically.

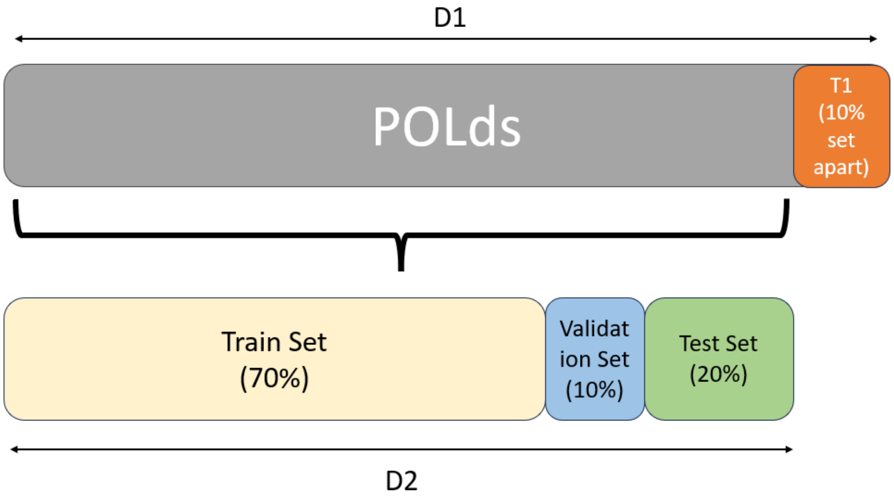


Figure 20. Dataset split for model development, evaluation, and testing.

6.2.2 Model Description

A computer vision model, which performs regression, was developed to tackle this problem. The model developed uses a convolutional neural network (CNN), which has twelve convolutional layers followed by pooling layers, to extract features from the input image. These extracted features are then flattened and passed to a fully connected layer that makes the predictions. The end goal of the model is to represent a connection between the various characteristics derived from the input photos and the relevant temperature values.

The model architecture employed is shown in Figure 21. These images are first resized to 240 × 240 pixels to reduce the computational cost and time. The input CCTV images are passed through the convolutional layers where several features such as edge detection, and corner detection are extracted by applying a set of learnable filters (kernels) to the image. These filters slide or convolve over the input data, performing element-wise multiplication and summing up the results to produce feature maps. These kernels produce an output feature map by taking the dot product of the filter weights and the corresponding pixel values in the image. This output is then passed through an activation function, in this case, ReLU (Rectified Linear Unit) to extract more complex information from these images. These output feature maps are then passed through the pooling layers which reduce the dimensionality while retaining the most essential features. The output maps are then flattened and passed through fully connected layers, giving out the predicted temperature values.

The neural network architecture encompasses several crucial layers, each contributing distinct functions to the image processing pipeline. The first input layer receives the resized input image, serving as the initial entry point for data. Following this, the convolutional layer engages, employing filters to identify and capture intricate image features, including edges and patterns. The batch normalization layer subsequently comes into play, normalizing the activations from the previous layer to attain a mean of zero and a variance of one. This normalization process enhances training efficiency. Integrating further, the max pooling layer strategically reduces the spatial dimensions of the input by selecting maximum values within pooling regions. By doing so, it optimizes training time while preserving the salient features crucial for accurate processing.

To prevent overfitting and facilitate robust generalization, the dropout layer introduces an element of randomness during training by randomly nullifying a fraction of input units. This safeguards against the model relying too heavily on specific connections, promoting a more adaptable and balanced learning process. At the pinnacle of this architecture, the dense layer performs intricate computations involving the dot product between input and weight matrices. This operation, followed by an activation function, orchestrates data transformation, which culminates in generating the final output, which would be the temperature prediction.

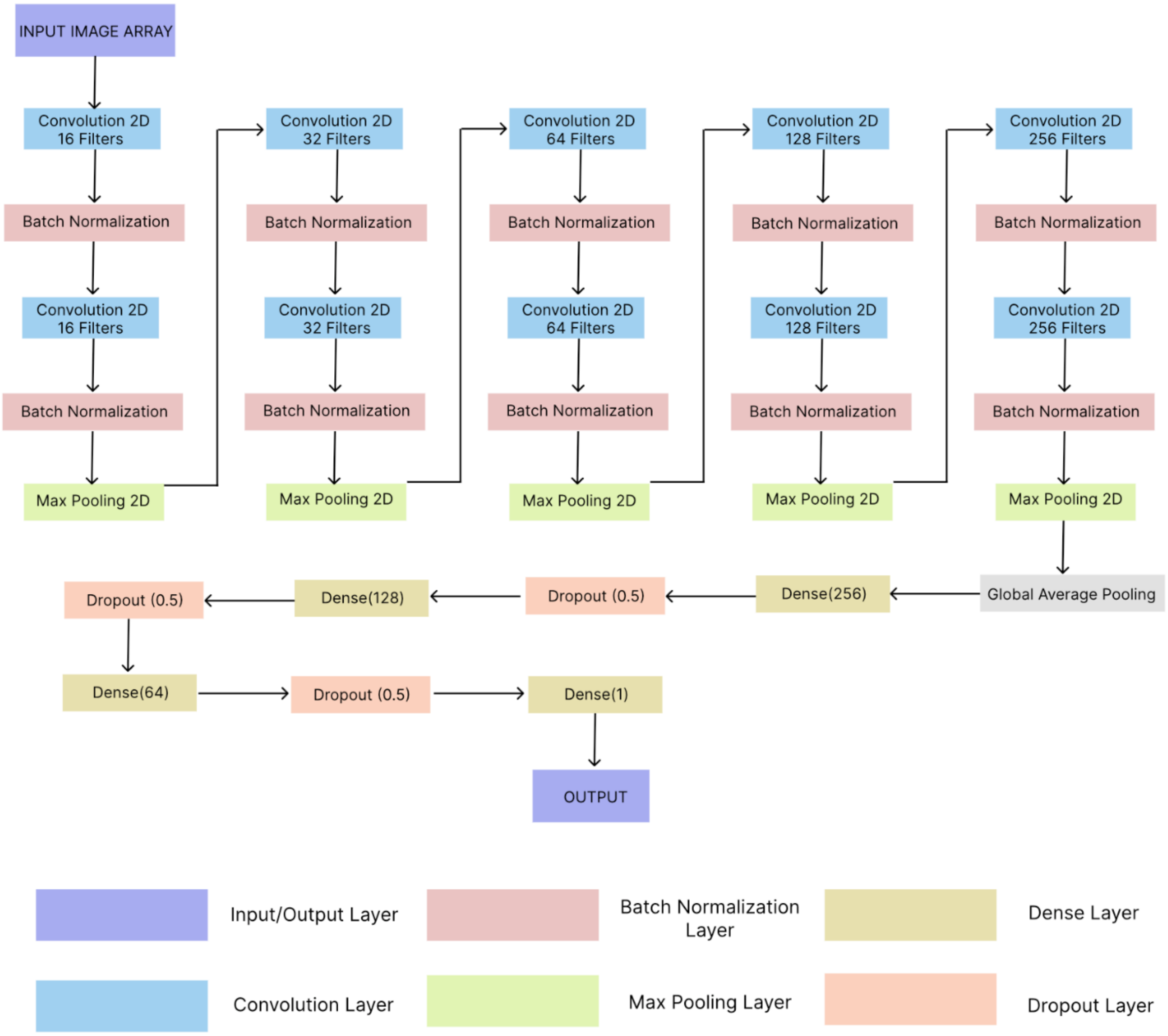


Figure 21. Detailed model architecture

In machine learning, the learning process is driven by a loss function, which serves as a metric for assessing how effectively an algorithm models the provided data. If the predictions significantly differ from the actual results, the loss function will yield a high value. Over time, with the aid of optimization functions, the loss function gradually learns to minimize the prediction errors. The model was trained using the mean squared error (MSE) loss function and the Adam optimization algorithm on a set of labelled images and their temperature values. The MSE loss function is given by the equation below.

$$MSE\ Loss = \frac{1}{N}\sum_{i=1}^{N}(y_i - y_i^*)^2$$

where N is the number of samples, y, and y* are the observed and the predicted road surface temperature values, respectively.

The model was trained on an Nvidia RTX A6000 GPU with 48 GB of memory and 10,752 CUDA cores. The step size was set at 32 and the learning rate was set as default which is 0.001. The training process implemented early stopping and a model checkpoint as two callback mechanisms. If the validation loss did not improve after a predetermined number of epochs (with a default patience of 7 epochs), early stopping was used to end the training. As the validation loss decreased, the model checkpoint was used to store the best model, guaranteeing the best model configuration is kept.

6.2.3 Evaluation Metrics

Coefficient of determination (R^2) and Root Mean Squared Error (RMSE) are used as the evaluation metrics to assess the performance of the model. These metrics are commonly used in regression analysis to gauge the goodness-of-fit and accuracy of the predictive model. R^2 measures the proportion of variance in the dependent variable that is explained by the model, while RMSE quantifies the average magnitude of the prediction errors. Together, they provide comprehensive insights into the model's predictive capability and precision, enabling a thorough evaluation of its effectiveness in handling the given dataset.

6.2.4 Bagging

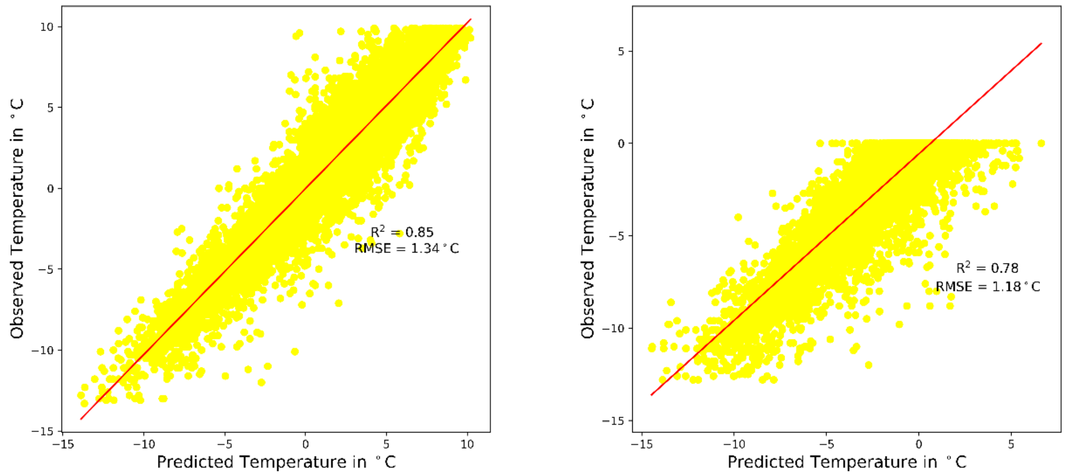
Bagging (or bootstrap aggregation) is an ensemble machine learning technique that employs a resampling technique to estimate the properties, or distribution of a statistic by repeatedly sampling from the available data with replacement. In simpler terms, bagging involves training several models with the same architecture that are trained on data obtained by sampling the original dataset with replacement. Once these models are trained, the final prediction is the average of the predictions by each model (for regression).

This approach is beneficial as it reduces the risk of overfitting to a specific dataset partition and provides a clearer picture of the model's generalization ability by averaging performance metrics over multiple resampled datasets instead of relying on a single train-test split. Ten different models were trained, each using 97,000 data points randomly sampled from the dataset of 137,900 data points with replacement. Each data point was treated as independent and identically distributed random variable. The final temperature prediction was the average temperature estimated by each of the models.

6.3 Results and Discussion

6.3.1 Performance evaluation on test dataset T1 and evaluation on temperature range from -12°C to 0°C

Each of the 10 models that were trained using the D2 dataset were tested using the reserved T1 dataset. The final predicted road surface temperature is the average of the predictions of each model. Figure 22(a) shows the scatter plot of actual temperatures (y-axis) and the predicted temperatures (x-axis). The red line represents the line of best fit. When all the data points lie exactly on the line of best fit, it means that the model is a perfect fit to the data, and the predicted value for each data point matches the observed value. The R^2 score on the line of best fit was 0.85 which shows that the true temperature and the predicted temperature agree with each other reasonably. This R^2 score shows that the model captures a substantial portion of the variance in the data. The RMSE obtained was 1.34°C. The RMSE value obtained indicates that the model predictions are reasonably close to the actual temperatures measured by the road surface sensor.



(a) (b)

Figure 22. Comparison between the observed and predicted pavement temperatures on the (a) T1 test set; (b) D1 dataset in the temperature range -12°C to 0°C

Figure 23 shows the R^2 score of each bootstrap sample of the model on the test set, T1. The plot shows that each iteration of the model has a worse performance compared to the aggregate result which is the mean of the prediction by each of the models. Bagging has two folds advantage, firstly, it overcomes the effects of the noise in the dataset (which temperature sensors are often susceptible to due to environmental effects) by averaging over multiple iterations of model trained on different samples and secondly, it reduces the variance in prediction when trained on a different dataset as it is already an average of predictions by models trained on different samples. The ensemble effect of combining multiple models and the reduction of overfitting by training on different subsets of data may also have contributed to the better aggregate result when compared to each individual model.

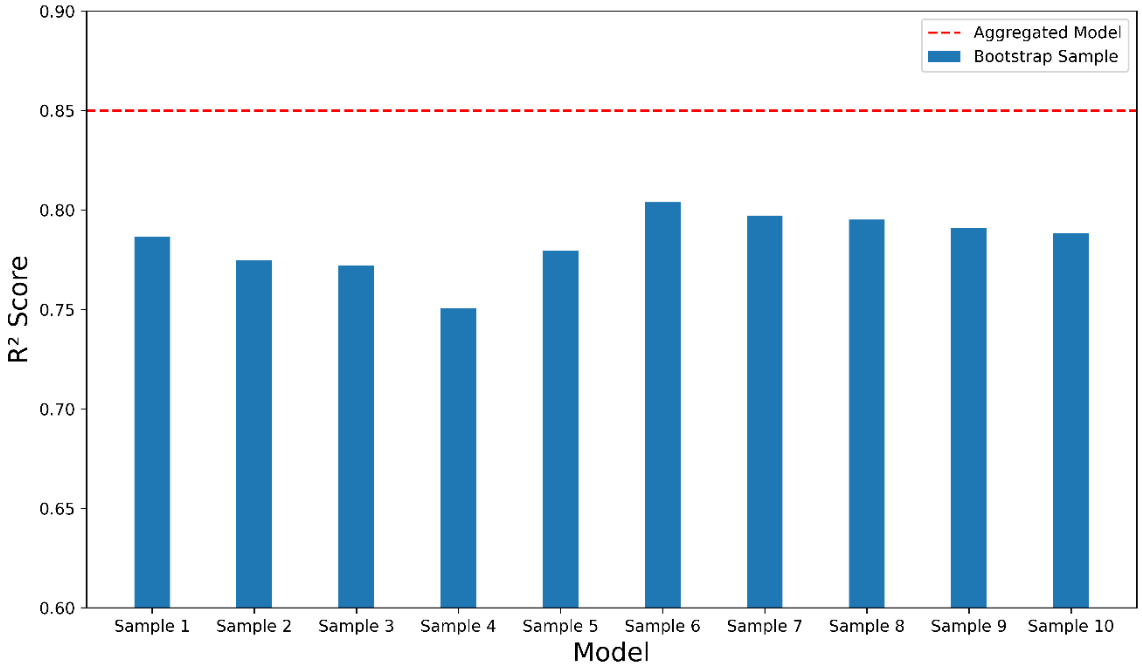


Figure 23. Graph showing the comparison of R^2 scores of test set T1 scored on each bootstrap sample. The red dotted line represents the performance of the aggregated model.

The road surface temperature would determine the effectiveness of the ice control chemical applied by determining the amount of ice it can melt. Usually, the lower the road surface temperature, the lower the melting rate of ice control chemicals. The amount of sunlight incident on an area, the air temperature and wind speed in that area, precipitation rate, and traffic volume can also influence the effect of the ice control chemicals. The present surface temperature and the trend of surface temperature are important factors that would help decide on an effectiveness snow and ice control treatment which include determining the type and application rate of ice control elements [4], [7].

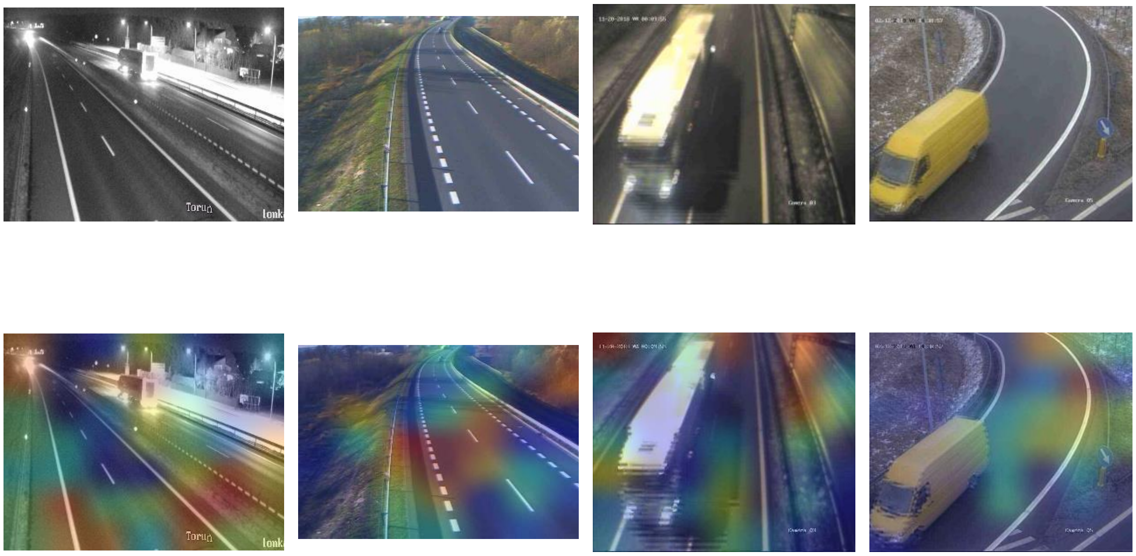
The surface temperature ranges that would be of major focus when determining proper ice and snow control strategy would be the temperature ranges from -12°C - 0°C (10°F - 32°F) [7]. The model developed is tested on road images which have these observed temperature ranges. 10,000 images are sampled from the POLds which fall between this temperature range. From Figure 22(b), the R^2 score obtained is seen to be 0.78 and the RMSE is 1.18°C which shows that the model performs reasonably well in predicting road surface temperatures that fall in this range.

Since this temperature range is crucial for determining the best course of winter road maintenance action, it is essential to ensure optimal performance of the model in this temperature range. While the performance metrics shown above indicate a decent level of performance, this can be improved by feeding the model with more accurate data points within this temperature range. This can help the model learn complex patterns and relationships which will then translate to better results. Experimenting with other weather variables that are relevant to road surface temperatures can also prove to be helpful.

6.3.2 Region of Interest

A Region of Interest (ROI) map was developed to identify the features that the model pays the most attention to in the images. This was important to ensure that the model could identify the road surfaces in the images. As shown in Figure 24 below, the red region shows the area of the image that the model gives the most importance, and the blue region corresponds to the area in the model that gives the least importance. The model mostly focuses on the roads which shows that a fair share of information is extracted from the road surfaces in the images. In the context of nighttime images (Figure 24(a)), which pose a challenge for the model due to their predominantly dark and monochromatic nature, compounded by graininess, the model's attention is often drawn towards prominent bright artifacts, which include the headlights of cars and the illumination from streetlights. Even then, a lot of the focus is on the road surface as seen in the heat map shown in Figure 24(a). In some of the more challenging situations, such as when a vehicle covers a major part of the road in the picture, such as in Figure 24(c) and (d), the model’s focus remains fixated on the road surface and circumvents the vehicle in the picture.

By disregarding the non-essential elements like vehicles covering a major part of the road surface, the model’s ability to demonstrate generalizability is improved. This allows the model to prioritize the road surface, even in challenging scenarios as shown in Figure 24(a), (c) and (d). The model shows less vulnerability to unimportant distractions in the scene by concentrating on the road surface. This robustness makes sure that the model keeps performing well in a variety of environmental circumstances, such as changing illumination, changing weather, or the appearance of unexpected items in the picture. The model's emphasis on the road surface demonstrates desirable characteristics, including consistency, generalization, and robustness, making it effective for the purpose of detecting temperature from road images.



(a) (b) (c) (d)

Figure 24. Original images (Upper) and their relative region of interest superimposed on them (Lower). The warmer colors represent higher levels of interest, and the cooler colors represent lower levels of interest.

6.3.3 Performance evaluation on different winter road conditions

The four primary road surface conditions observed during winter encompass ‘dry’, ’wet’, ‘snow’, and ‘ice’ conditions. These four conditions were used as a testing ground to assess the model's ability to effectively generalize across all of them. For this, 4000 images each for ‘dry’, ‘wet’ and ‘snow’ conditions were sampled from dataset D1. Only 120 images were accessible for the ‘ice’ condition from dataset D1, which resulted in a smaller representation compared to the other road conditions where at least 4,000 images were available each. Figure 25 represents the performance metrics of the model on each of these road conditions.

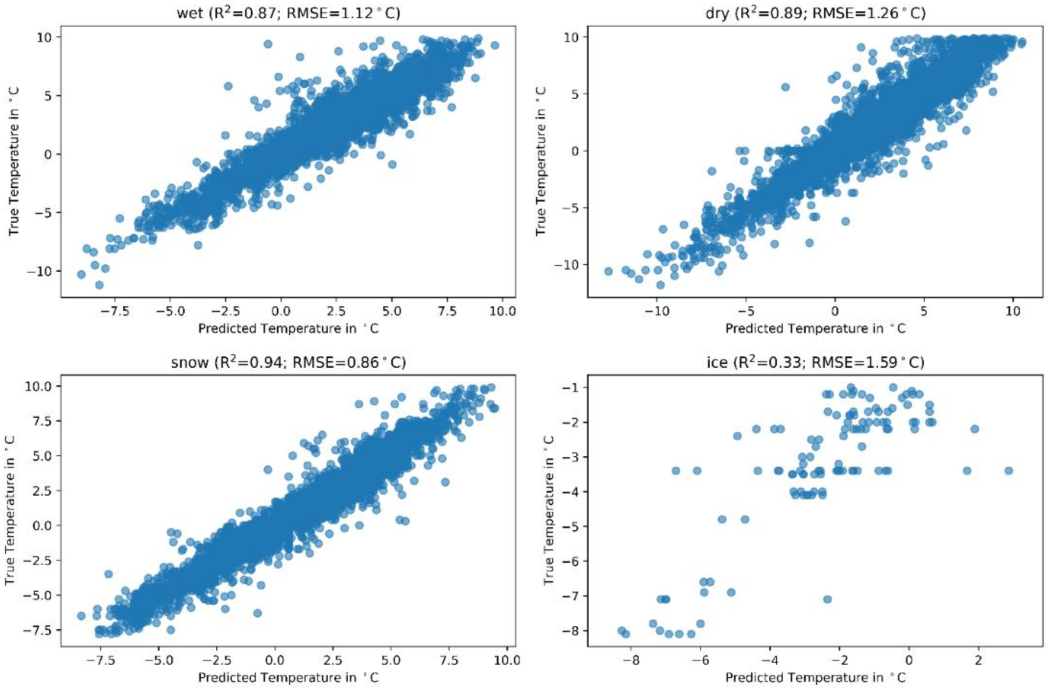


Figure 25. Performance evaluation of the model on different surface conditions observed in winter months.

It can be observed from Figure 25 that the model performs adequately well in predicting the road surface temperatures when the surface conditions are ‘snow’, ‘dry’ and ‘wet’. However, the model performs significantly worse when it comes to detecting pavement temperatures in ‘ice’ conditions with an R^2 value of 0.33 and RMSE of 1.59°C. This can be attributed to the scarcity of ‘ice’ images in the dataset which impacts the model’s ability to generalize effectively for this specific condition, leading to a dip in performance when encountering ‘ice’ road images.

These results show that the model performs well in ‘wet’, ‘dry’ and ‘snow’ conditions, which underscores that the more the model sees the better it predicts. Enhancing the model's proficiency in predicting images under 'ice' road conditions could be achieved through augmenting the dataset with more samples from this particular condition. This augmentation would enable the model to discern underlying relationships more effectively, subsequently refining predictions and enhancing overall accuracy.

These results show that the model developed can capture a significant portion of the temperature variations in the data and offers a reasonably good fit for the observed temperatures. The relatively low RMSE value indicates that the model’s predictions are generally accurate and close to the observed values. The developed model holds particular significance for the highway agencies in road surface temperatures estimation, especially during the winter months. It shows potential to be a valuable tool for accurate temperature predictions when traditional road surface sensors may be affected or damaged due to harsh winter conditions.

6.4 Conclusion

A computer vision technique to estimate the temperature of road surfaces using the images captured by CCTV cameras was developed. The model, TimgsNET, achieved commendable metrics in its temperature prediction for road surfaces, boasting an R^2

value of 0.85 and an RMSE of 1.34°C, both of which are indicative of its strong performance. The Region of Interest map also shows that the model manages to identify features from the road surfaces in these images and disregard other artifacts such as vehicles obstructing the camera view. This makes the model generalizable, as the capability of the model to isolate roads in images of varying quality and conditions makes it robust to different surroundings which are not in the regions of interest.

The performance of the model was evaluated in the temperature range of -12°C to 0°C, which is considered vital in deciding the method of ice control treatment to be used. The model achieved an R^2 score of 0.78 and an RMSE of 1.18°C when tested on images in this temperature range, which underscores its robustness and accuracy in capturing temperature variations in this range. The model is also evaluated at different winter road conditions of ‘dry’, ’wet’, ’snow’, and ‘ice’ conditions. The model exhibited satisfactory performance across all conditions except for 'ice', with an R^2 value 0.33 and RMSE of 1.59°C. This disparity in performance is attributed to the limited number of 'ice' condition images within the dataset D1, which resulted in insufficient representation for effective learning.

The model developed in this study offers significant potential to assist the highway agencies as an auxiliary tool for predicting road surface temperatures from images in cases where the road surface sensors are damaged or nonfunctional. In such cases, the model shows great promise, by utilizing images to estimate the road surface temperature. This innovative solution can enhance the agency’s ability to maintain efficient and safe road networks, providing crucial information even when traditional sensing systems encounter disruptions. This technique can also be employed in rural and remote areas which often lack RWIS infrastructure to improve their quality of life and travel in winter months.

However, it remains a question how this model would perform in a condition that is totally alien compared to the training set that it sees. If the model encounters a road surface image it does not identify, the errors in the predictions might be high. This begs for newer and more robust image augmentation techniques which can challenge the model to identify features within a much different quality of images and surroundings. Future research could also focus on collecting a more diverse data set and training the model on that dataset. Enhancing the model architecture by incorporating more input features such as ambient air temperature may also help in improving the predictions. By continuously refining and innovating on these fronts, the model's capabilities can be advanced and its practical applicability in a wide range of road surface temperature monitoring scenarios can be improved.

CHAPTER 7

CONCLUSIONS

This thesis focused on the development of machine learning and computer vision models to predict road surface temperatures and conditions. The findings emphasize the crucial significance of accurately predicting the road surface temperatures and conditions to ensure the safety and efficiency of transportation systems, particularly in the presence of snowy, slushy, or icy road conditions which contribute to a substantial proportion of weather-related vehicle crashes in the United States. Timely and accurate information is crucial for successful highway winter maintenance programs, particularly for snow and ice operations. It enables informed decision-making regarding the appropriate application of anti-icing and deicing chemicals.

By leveraging historical meteorological data, road surface sensor data, and real-time road surface image data, we successfully constructed models capable of reliably forecasting road surface temperatures and conditions. The integration of these models into existing road weather information system (RWIS) networks holds immense potential for enhancing the accuracy of predictive information accessible to transportation systems.

The computer vision models developed in this study offer an additional dimension by detecting real-time road surface conditions, including dry, wet, ice, snow, and slush.

This augmentation provides further improvements in transportation safety and efficiency. By combining these computer vision models with temperature prediction models, a comprehensive and dependable understanding of road surface conditions can be achieved. The integration of the developed machine learning models and computer vision models offers the potential to establish a cost-effective and spatially unconstrained road weather information system (RWIS). This innovative system addresses the limitations encountered by traditional fixed RWIS stations and, notably, can extend accessibility to rural communities. The inclusion of the model that can detect temperatures from images can potentially help areas that lack the resources to have embedded pavement sensors.

The integration of these models into RWIS networks offers the potential to significantly enhance the safety and efficiency of transportation systems. The accurate prediction of road surface temperatures and conditions will enable authorities to proactively implement appropriate measures and strategies, reducing the risk of weather-related vehicle crashes and ultimately saving lives.

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