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Developing a Solution to Improve Road Safety Using Multiple Deep Learning Techniques

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Abstract

The number of traffic accidents caused by wet or icy road surface conditions is on the rise every year. Car crashes in such bad road conditions can increase fatalities and serious injuries. Historical data (from the year 2016 to the year 2020) on weather-related traffic accidents show that the fatality rates are fairly high in Korea. This requires accurate prediction and identification of hazardous road conditions. In this study, a forecasting model is developed to predict the chances of traffic accidents that can occur on roads affected by weather and road surface conditions. Multiple deep learning algorithms taking into account AlexNet and 2D-CNN are employed. Data on orthophoto images, automatic weather systems, automated synoptic observing systems, and road surfaces are used for training and testing purposes. The orthophotos images are pre-processed before using them as input data for the modeling process. The procedure involves image segmentation techniques as well as the Z-Curve index. Results indicate that there is an acceptable performance of prediction such as 65% for dry, 46% for moist, and 33% for wet road conditions. The overall accuracy of the model is 53%. The findings of the study may contribute to developing comprehensive measures for enhancing road safety.

Keywords: *Meteorological Data, Orthophoto Image Data, Road Surface Data, Deep Learning*

1. Introduction

Traffic accidents due to rain or icy roads occur steadily every year. Rainy or icy road surfaces have a lower coefficient of friction than normal road surfaces. This issue greatly increases the possibility of traffic accidents such as increased braking distance and slipping [1]. Therefore, road surface conditions pose a great threat to safe driving, so a method to prevent them is needed. In this study, we intend to develop three deep learning classifier models that can predict road surface conditions. Three different types of data are gathered for the task; Meteorological, orthoimage, and road surface conditions are used for the training and testing of the deep learning models. The results of predicting the road surface conditions with this model can contribute to the reduction of the incidence of traffic accidents by enabling preemptive response to the route.

According to statistical data from the Traffic Accident Analysis System (TAAS) from 2016 to 2020, the injured number rate of individuals in accidents is at least one person per accident, and this rate is believed to be increasing. Moist, wet, slush, and ice conditions have been found to have a higher fatality rate than dry or snowy conditions, with dry conditions being the least deadly of all. This has led to the idea of developing a

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forecasting model that could be applied to help reduce the number of fatalities or injuries on the roads. The model would be designed to give warnings of hazardous weather conditions, enabling drivers to take extra caution when necessary. This could also lead to better road maintenance and design, as well as improved safety measures, such as additional guardrails or signage to help drivers adjust their speed to the conditions. With the application of this forecasting model and additional safety measures, the number of fatalities or injuries due to accidents on the roads could be greatly reduced.

While driving, we may come across information boards that guide traffic jams ahead on highways or navigation systems that provide traffic accident information along driving routes. Because information is provided in advance, is possible to slow down or pay more attention to driving. Therefore, if the driver can know information about the road surface condition in advance, the vehicle speed can be lowered in advance, thus, reducing the accident rate according to the road surface condition [21]. This study aims to provide a new approach to the prevention of traffic accidents due to road surface conditions. As mentioned above, in every traffic accident of every road condition there is at least one injured person according to the TAAS. Also, we prove that the worse the condition is, the more the fatality rate is going to show.

This paper is organized as follows. In the second section, the paper describes related literature regarding the use of deep learning techniques associated with the impact of road conditions and weather on traffic accidents. It then discusses data collection and processing in terms of orthophoto images and road surface conditions. This is followed by a model development taking account of weather, space, and road conditions. Data on orthophoto images, automatic weather systems, automated synoptic observing systems, and road surfaces are explained. The orthophotos images as input data in the modeling process are discussed. In the final section, we summarize the main conclusions.

2. Literature Review

During our literature review, we found that road conditions are gathered by (1) optical devices, (2) radar devices, (3) infrared spectroscopy devices, and (4) vehicle monitoring devices. [13, 14, 17, 19, 20] used state-of-art deep learning algorithms for detecting road surface conditions. [13] introduced a mmWave radar device to enable robust and practical road sensing to classify surface types (gravel, asphalt) and conditions (dry, wet). However, during its development, mmWave had noisy measurements due to its high sensitivity caused by car vibrations. To fix the issue, a supportive cross-modal supervised model is developed to sense road surfaces using mmWave measurements. This approach achieved a 98% accuracy in classifying road types and 99% accuracy for road conditions.

[14] presented a 2-stage road friction estimation system using front-view camera images captured from vehicles. Stage 1 applied a convolutional neural network model to filter only the regions of interest for classifying road surface conditions achieving a 97% accuracy. Stage 2 applied a rule-based model that relies on domain-specific guidelines to separate images with high, medium, and low road friction estimates achieving an 89% accuracy. This model used publicly available data sets to contribute to future research and development.

[17] presented a road surface classification deep learning model-based convolutional neural network architecture. This convolutional neural network is trained with a tire-pavement interaction noise (TPIN) data set that reflects the surface profile properties of the road and its texture properties. Compared to images, which can get noise easily by factors such as illumination and obstacles, TPIN is robust because the signal is not affected. The model's average accuracy is near 92% for dry asphalt and snowy roads. [19] makes a comparison between the performance of machine learning and deep learning algorithms when image noise is caused by sunlight glare and residual salts are present. The machine learning algorithm faces challenges when classifying. However, this study implements a pre-trained convolutional neural network (VGG16) model to address these

challenges. As a result, deep learning applications achieve a better classification performance in comparison to implemented machine learning algorithms.

[20] proposed a real-time winter road surface condition pre-trained model (ResNet) monitoring system that automatically updates. Instead of using vehicle cameras, it makes use of fixed traffic/weather cameras. The evaluation is done with an extensive set of experiments to test the accuracy and generalization of each model. Also, it applies transfer learning to fine-tune each of the pre-trained models. As a result, the accuracy of re-training the pre-trained models using data from all new cameras with all road surface classes presented a significant improvement than without re-training.

[15] reviewed several research works on non-contact road surface condition detection systems. According to this study, infrared spectroscopy methods constitute effective means of non-contact road surface conditions detection because they presented characteristics such as rapid detection, high accuracy, and precision, and are practical. Because of day-night, seasons, or other related issues, infrared spectroscopy experienced an accuracy decrement. However, this study presented two possible solutions for the problem. Modulated active light source illumination and targeted de-improved data acquisition module approach are one of the ways to improve the above problems at the system level.

[16] compare the field measurement results of two different sensors (RCM411 and MARWIS) with laboratory experiment results previously performed with an On-Board Diagnostics (OBD-II) winter road assessment tool and an experimental radar sensor. The results of the two sensors and laboratory experiments showed a significant correlation. OBD-II showed that can be used as a supplementary tool in the assessments by customizing it to detect road conditions. The advantage of OBD-II is that it gives information about the vehicle that other sensors do not calculate. On the other hand, experimental radar shows the need for more investigation because if the surface roughness experiments with the smallest changes, it causes a lot of noise in the measurements.

[1, 2, 3] proposed methods that can contribute to vehicle safety by analyzing the correlation between weather and road surface conditions. A road surface sensor device in a vehicle measured the road surface condition. The collected data (sensor data) used the weather information of the nearest location (Automatic Weather System and Automated Synoptic Observing System) to confirm the correlation between weather and road surface condition and between road surface condition and friction force. In the study, a Random Forest Classifier model to predict road conditions is developed. The overall precision, recall, and F1-score (harmonic mean of the precision and recall) of the Random Forest Classifier model is 95% in predicting dry, wet, moist, slushy, and icy road conditions. Also, a deep learning prediction model was developed for the same purposes.

Research in [4] was conducted to implement a system capable of providing road surface condition prediction results through real-time analysis. The data used for the study was combined with road surface state information by attaching a road surface sensor to a moving vehicle and meteorological information from a meteorological station near the location of the collected road surface condition. The process of implementing an analysis system that can classify road surface conditions using meteorological data alone by finding a statistical model capable of classifying road surface conditions conducted similarly to our research.

In [9], empirical analyzes are used to determine the relationship between the risk of traffic accidents and the age of the road surface. However, they do not evaluate the degree of road safety provided by the pavement. Physical signs of pavement damage are strong indicators of vehicle stability and comfort. This limitation makes it impossible to develop a pavement management strategy that could improve driving safety. This study empirically analyses the relationships between pavement conditions and crash risk.

[5, 18] trained a support vector machine algorithm to detect road surface conditions. [5] developed a support vector machine multidimensional analysis algorithm for detecting road conditions such as dry, wet, snow, and

ice. This study gathers image data from a camera mounted in a vehicle and analyses the image data by polarization coefficients and wavelet transform. Therefore, achieving considerably high performance when predicting ice conditions (unsafe conditions).

[18] developed a support vector machine model that categorizes 5 types of road conditions (dry, wet, snow, ice, and water). Images are segmented in 9-dimensional color eigenvectors and 4 eigenvectors are extracted to construct road surface state characteristics. To improve the algorithm's accuracy, a grid searching algorithm and a Particle Swarm Optimization (PSO) algorithm are used. Therefore, achieving 90% accuracy.

3. Data Collection and Processing

This section explains how the data is gathered and how the data was preprocessed for training deep learning models.

3.1 Data Collection

Weather data, previously collected road surface state data, and orthoimage data are used to predict road surface conditions. For meteorological data, Seoul-Metropolitan area precipitation, snowfall, and temperature data are extracted from Automatic Weather System (AWS) and Automated Synoptic Observing System (ASOS) provided by the Korean Meteorological Administration and used as train/test data for the model. The road surface state data is used as label data by matching the label representing the road surface condition with the meteorological information at the time of sensor measurement. The orthoimage image uses the image provided by the National Geographic Information Institute (NGII) and extracts the spatial characteristics of whether the image entered as input data is an area with many roads or a mountainous area, and uses it as training data for the model.

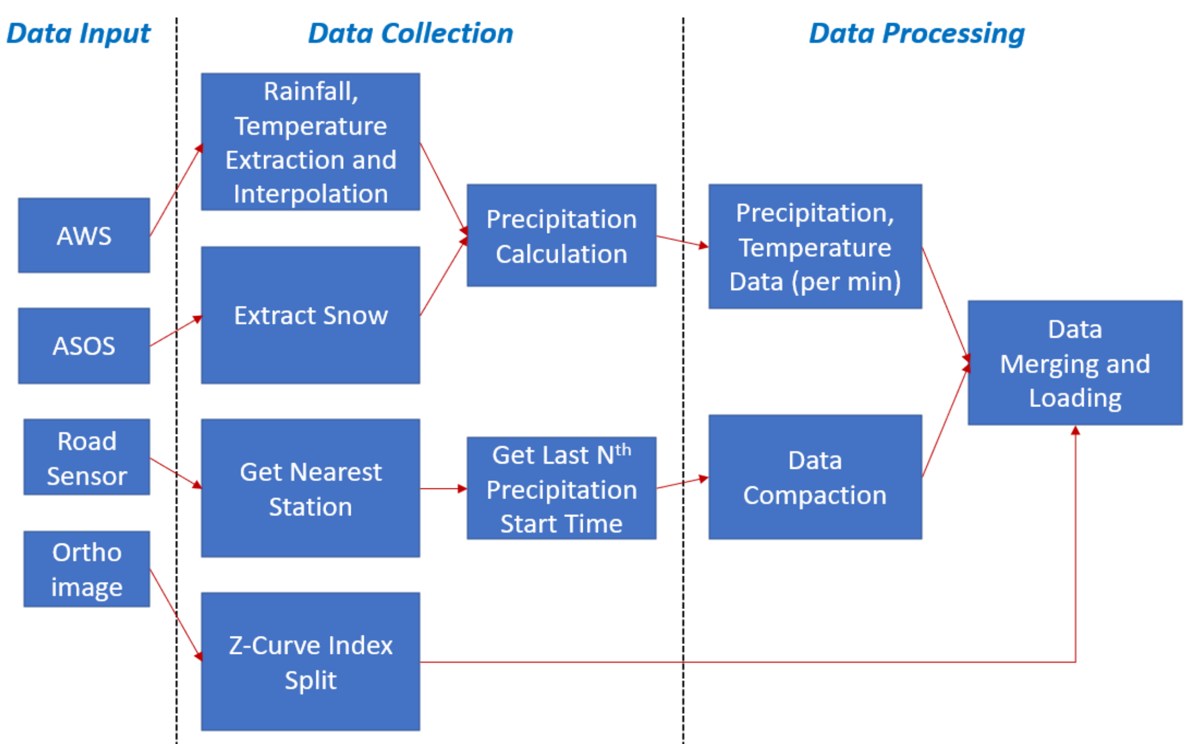

Figure 1. Data Collection and Processing Flow Chart

3.2 Data Processing

3.2.1 Orthophoto images

Orthophoto images are split using Z-Curve Index. Z-Curve-based image segmentation divides the image area that matches the Z-Curve Index value in a 1:1 ratio and returns the segmented image file with the Z-Curve Index level and the value used for image segmentation as the file name. Since the Z-Curve index itself is an ordering technique, local optimization (optimized only for a specific region) is required, so an upgrade is necessary. Therefore, we attempted to change the existing Z-Curve Index value to an image with more spatial explanatory power, and it was confirmed that the actual performance improved. As a reference, from level 1~10, spatial level 8 had the best accuracy than other levels of spatial resolution. Figures 2,3 show that the greater level of spatial resolution, the more information is gotten from x-segmented images.

Figure 2. Image Split Level 2 in Z Curve Index

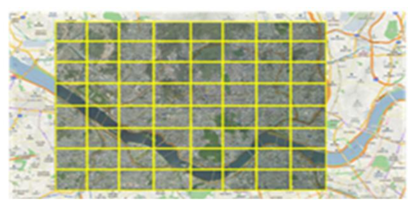

Figure 3. Image Split Level 3 in Z Curve Index

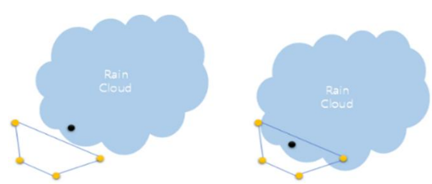

Figure 4. Nearest N-Gon

Figure 5. Delaunay Triangulation

3.2.2 AWS and ASOS

Interpolation techniques, such as Nearest N-Gon-based interpolation and Delaunay Triangulation, are used to fill in missing values in meteorological data, which can have a detrimental effect on the accuracy of the model [7, 10, 11]. (Fig 4) Nearest N-Gon-based interpolation entails creating n-gons around the sensor observation points, with the interpolation process utilizing the sensor values at each vertex to predict the missing values. The n-gon is a mathematical object that is composed of a set of points arranged in a specific shape and form, allowing for a more accurate estimation of the missing measurements. (Fig 5)

Delaunay Triangulation, on the other hand, involves creating triangles that connect all the points and is often used in 3D graphics and 3D reconstructions. This technique makes use of a triangular mesh, which is created by connecting the points of the data set and forming triangles. The triangles are then used to approximate the missing values for the data set. It is also worth noting that both techniques are widely used in meteorological forecasting, given the amount of missing data that can occur in these scenarios. Interpolation techniques can be used to fill in these missing values reliably and accurately, thus providing meteorologists with more accurate predictions for weather-related events.

After filling in the missing values of AWS, the next step is to calculate the precipitation using the amount of rainfall and snowfall corrected for missing values. The precipitation here is the amount of rain or snow. The snowfall precipitation is generally considered to be 1mm precipitation for every 1cm of snowfall. After converting the amount of snow accumulated in one hour into precipitation, the value is divided by 60 minutes and added to the amount of rainfall per minute as shown in Eq 1. Based on the reference AWS station, the precipitation of nearby ASOS stations is added. Since precipitation is added based on AWS stations evenly distributed in Seoul, more accurate meteorological data can be taken into account when predicting road surface conditions. After calculating the snow precipitation, ASOS and AWS precipitation are summed.

$$PrecipitationPerMinute = \frac{(snowPerHour \div 10)}{60} \qquad \text{(Eq 1)}$$

3.2.3 Road Surface Condition

This paper examines the effect of past rainfall on road conditions in Korea from 2015 to 2018, using a sensor attached to a vehicle and GPS coordinates. In particular, the study focuses on the impact of rainfall on icy roads, as well as the need for a sufficient amount of time to pass before the effects of this precipitation can be measured. The data collected reveals that even when there is no rain or snow within 12 hours of icy road conditions, rainfall from more than seven days ago can still affect the current road condition. To prevent overfitting and ensure accuracy, the data is compressed by taking into account the collection point, road surface condition, and proximity to the observatory.

Furthermore, this research draws attention to the importance of considering the long-term implications of rainfall on icy roads, as well as the need to take into account the delay between rainfall and its effects. This is especially pertinent in regions with extreme climates, as the weather and its subsequent impacts can be unpredictable and difficult to predict. Taking all this into consideration, this study provides valuable insight into the impact of past rainfall on current road conditions in Korea, and the importance of considering the delay between the precipitation and its impact. The results of this study are essential for understanding the role of precipitation in icy road conditions, and for developing strategies for minimizing the risks associated with such conditions.

Table 1. N-th Precipitation Points

Total days	Less than 12 Hours	Less than 2 day	Less than 2 days	Less than 3 days	Less than 4 days
41 days	4 days	9 days	6 days	6 days	6 days
	Less than 5 days	Less than 6 days	Less than 7 days	More than 7 days	
	3 days	3 days	1 day	7 days	

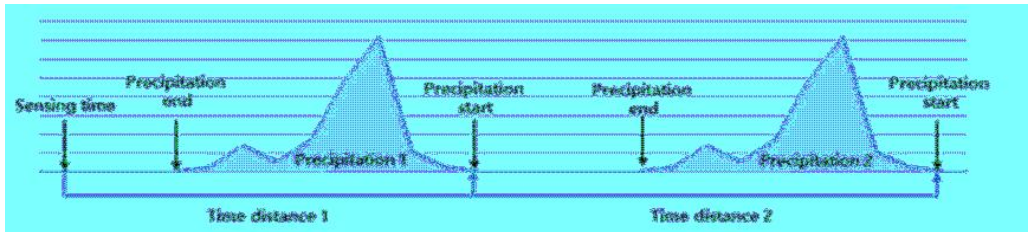

Figure 6. Precipitation Start and End Distance

3.2.4 Training and Testing Data

As shown in Figure 7, the preprocessed weather data (AWS, ASOS) and road surface state data are merged into a single dataset. For weather data, all data from the start of the previous Nth rainfall to the point of sensor measurement will be used as input data. If the sensor measurement time is 1440 minutes from the start of the previous Nth rainfall, the shape of weather data used as input is (1, 1440).

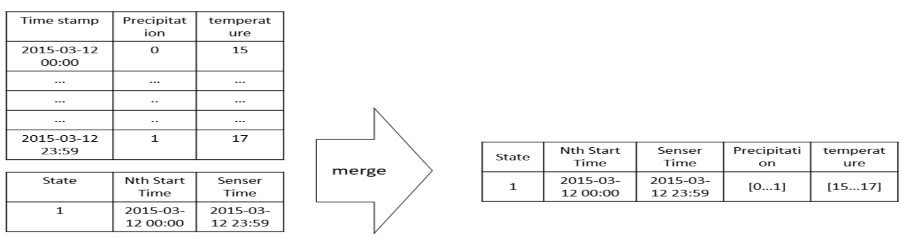

Figure 7. DataSet Merging Process

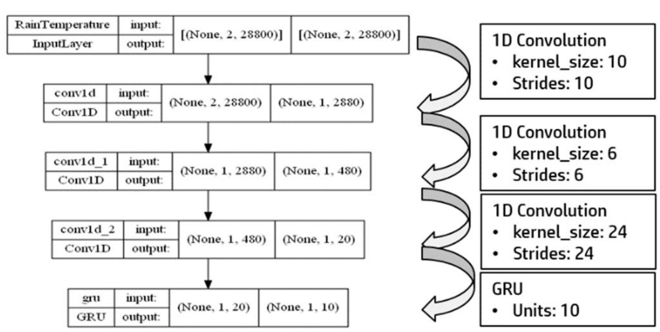

Figure 8. Modeling Structure of Weather Cluster Classifier

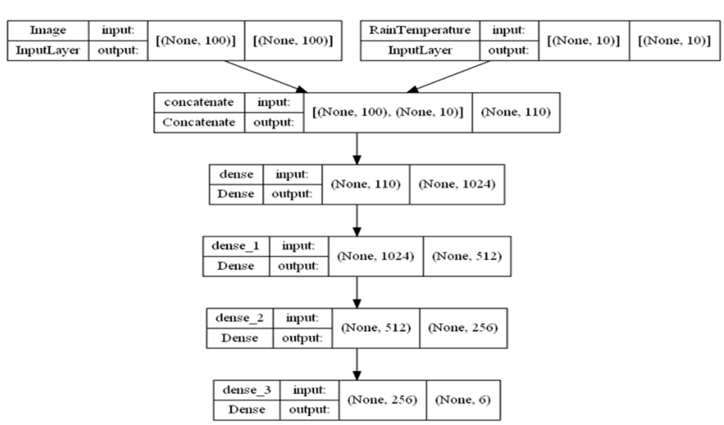

Figure 9. Modeling Structure of Road Condition Classifier

4. Model Development

This section explains the models used for making road surface state predictions.

4.1 Weather Classifier

The meteorological data used previously cannot be used for statistical values. In addition, there is no difference in the value of weather data for each road surface condition, and it is judged that it is difficult for the model to classify the road surface condition when used as input data to a road surface condition classification model. The purpose of the model itself is to extract significant features and meanings of the preprocessed meteorological data. As shown in Figure 8, the Model input is the result of concatenating the precipitation and temperature into a 2D array of length 28,800. The 28,800-long length is selected arbitrarily. The Nth precipitation start time from the point of observation of the road surface sensor is 20,065 minutes on average, and its standard deviation is 10,175 minutes.

The output is a 1D array of length 10 with the data features and meanings for the Road Condition Classifier. Weather data is time series data. The model configuration uses a 1D convolution layer and a gated recurrent unit (GRU) layer, which is widely used for time series data. We perform dimensionality reduction in one day through three 1D convolution layers. 1st Layer: 1-minute unit data is expressed as one 10-minute unit value through convolution. Second Layer: 10-minute data is expressed as one hour-unit value through convolution. Third Layer: Express 60-minute data as one day-unit value through convolution. Build a model using the GRU Layer, which is good for processing time series data.

4.2 Spatial Classifier

Some Pre-trained models were considered during this research such as AlexNet, GoogleNet, Wgg16, ResNet, and InceptionV3. However, the model that showed the best performance and the lowest model complexity is AlexNet. The main purpose of this model is to extract spatial characteristics from orthophoto image data. The spatial characteristics of the image entered as input data are extracted. These characteristics are such as an area with many roads or a mountainous one. The utilization of the 2D-CNN model is useful for finding image patterns since the utilized data are images. The advantage of using a pre-trained model is that has already been trained and can derive an output. Because it takes a long time to learn from image data, using a pre-trained model reduces the development time. The model input is the 8-level spatial resolution segmented and resized (224, 224, 3) image. The final output of the model is an array containing an analysis of the spatial features of the images for the Road Condition Classifier.

4.3 Road Classifier

The purpose of this model is to classify the road surface conditions into labels from 0 to 5 by mixing meteorological data and orthophoto image data. As shown in Figure 9, the output of the Weather Model is a 1D-Array with significant features extracted from meteorological data. The output of the Spatial Model is a 1D-Array with extracted spatial characteristics of orthophoto image data. These two outputs are used as input for training the Road Condition Classifier. The output of the model is a One-Hot encoding representation of the 6 different labels that the model can predict (dry, moist, wet, slush, ice, snow).

5. Results

As mentioned in the introduction, the performance of our model was lacking. Learning could not be properly performed because there was no snow label value in the collected road condition data, so the snow was removed from the test value. The other labels were left untouched. However, as Figure 10 shows, the performance of the model in predicting slush and ice was nonexistent. This is because the data used for training the model lacked slush and ice data points. During our analysis, the data that was mostly gathered was mainly dry, moist, and wet data points. This issue causes an unevenness or inequality of the input data when training the models.

The prediction performance of each label according to Table 2 is 65% for dry, 46% for moist, and 33% for wet conditions. The overall accuracy of the model is 53%. Table 3 shows that the performance of other state-of-the-art studies is better than our developed model. However, [13, 14, 17, 20] only focused on a few labels, resulting in higher accuracy and generality of the data than in our study. The more labels added to the model, the more complex the data processing and model fine-tuning become. However, in [2] the overall accuracy of the model in all labels, except snow, is outstanding. This approach is based on a random forest classifier (machine learning) algorithm, not neural networks as in this study.

Table 2. Prediction Performance of Labels

	Precision	Recall	F1-Score	Support
Dry	65%	62%	64%	9798
Moist	46%	41%	43%	6215
Wet	33%	44%	37%	1727
Slush	0%	0%	0%	0
Ice	0%	0%	0%	0
Accuracy			53%	17740
Macro Avg.	29%	29%	29%	17740
Weighted Avg.	55%	53%	54%	17740

Table 3. Developed State-of-the-art Studies and Our Study Performance

Road Conditions	Our Study	[13]	[14]	[17]	[20]	[2]
Dry	65%	99%	96.98%	86.25%		97%
Moist	46%					92%
Wet	33%	99%	97.34%			95%
Slush	0%					81%
Ice	0%					92%
Snow	0%		99.08%	97.85%	91.46%	

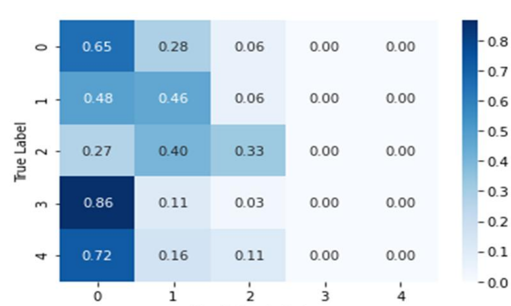

Figure 10. True and Precision Label Matrix

One of the main issues of this project is the performance when classifying the different types of road surfaces. The model needed to distinguish between the six labels. However, the main problem is that there is insufficient data for some labels, leading to inequality when classifying road surface conditions.

We divided the solutions into primary and secondary. The primary solutions are: (1) fixing the collection and processing part; (2) when gathering new data, applying a more efficient method than the previous method. The most important step for developing an AI model is collecting and processing data. This first step is crucial for boosting the accuracy of the model, as it can gather the necessary features and patterns from data to classify between the six labels.

Table 4 reveals that snow, slush, and ice data are the labels with the lowest percentage share compared to dry, moist, and wet. This indicates that, while the model has a good understanding of the different conditions, it is lacking in the ability to differentiate between slush, ice, and snow. As such, if new data were to be collected, it would be prudent to ensure that it contains significantly more information about slush, ice, and snow, to give the model more learning features. This would enable the model to become more adept at understanding the subtle nuances between the different labels, thus making it more accurate in its predictions.

Table 4. Road Surface Data (8Am~8Pm November 20 2015~ March 31, 2016)

Road Condition	Dry	Moist	Wet	Slush	Ice	Snow
Data Amount	3,846,231	1,520,736	651,345	5,928	154,018	0
Amount Rate	62.25%	24.61%	10.54%	0.01%	2.49%	0%
Whole Data	6,178,258					

The secondary solutions are (1) changing the parameters of the model; (2) developing a new model. During the improvement of the model, we aim to change parameters such as epoch, neuron, batch size, and others. The accuracy of the models oscillated between 50-60%. This means that the preprocessing phase is crucial, so the improvement of the model parameters can be helpful. We tested several other models' performance, and changing the model could lead to a greater improvement if a model with a better fit for these kinds of data is found.

6. Conclusions

This study was conducted to develop a road surface condition forecasting method for preventing traffic accidents caused by the impact of weather on different road conditions. Various methods were employed to process the collected data, such as the Delaunay triangulation, Nearest Nth Gon, and also the adaption of snowfall into a metric that could be generalized and added to the rain precipitation to compute the total precipitation. This method allows for an effective evaluation of the road surface condition, as well as the ability to forecast its future condition, which can prove to be invaluable in the prevention of traffic accidents. Furthermore, the collected data can be used to identify possible trends in the weather, allowing for a more accurate prediction of the conditions in the future. This information can be used to inform road users of potential accidents, as well as to prepare for any potential risks before they occur.

One of the main difficulties of the project was the long arrays used for training the model and also the preprocessing of the orthoimage data. The orthoimages utilized the Z-Curve index for splitting the image and gathering the most relevant image points for training the model. The best spatial level is 8 for the data collected in this study. To ensure accuracy, numerous tests were made on different spatial levels to determine the best fit for the data. While analyzing the indexed images, the images presented blurriness. This was a major concern since it led to a decrease in the performance of the model. As a result, this issue limited the model from gathering the most relevant information from the image and decreased the performance of our model significantly. To mitigate blurriness, solutions such as image smoothing, image sharpening, and contrast stretching can be applied.

In conclusion, although the performance of the model is not high, the results of this study can be used for the development of various systems that can predict the degree of road slippery to drivers in advance according to weather forecasts. This can contribute to improving vehicle safety and reducing social costs due to traffic accidents.

Acknowledgment

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