

Road Wetness Estimation Using Deep Learning Model [†]

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Abstract: Accurately identifying road conditions, particularly wetness, is crucial for ensuring road safety and enhancing vehicle performance. We conducted road surface classification and road wetness estimation using state-of-the-art deep learning models in this study. Raspberry Pi Model 4 was used to classify road surfaces and estimate road wetness. SqueezeNet, a lightweight convolutional neural network, was used to recognize wet and dry road surfaces with an accuracy of 90%. The ENet model, known for its efficiency in semantic segmentation tasks, was used to estimate the degree of wetness, categorizing roads into damp, wet, and very wet roads. The ENet model showed an accuracy of 90.48%. The efficiency of the deep learning models in road surface wetness monitoring was validated using a confusion matrix created with the margin classifier. A total of 300 images per category were used for training, amounting to 1200 in total. A total of 20 testing images were used for road surface classification and 21 for road wetness estimation. The results highlighted the robustness and applicability of SqueezeNet and ENet models in estimating diverse environmental road conditions.

Keywords: road surface condition; road wetness estimation; SqueezeNet; ENet; confusion matrix



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1. Introduction

Rain causes terrain or roads to be wet for vehicles. Drivers must adapt to the wet surface to avoid accidents. According to the most recent Metro Manila Accident Reporting and Analysis System (MMARAS) [1], more than 26,000 accidents occurred in the National Capital Region during the wet months of 2020. From June to October, over 40% of all accidents took place. Wet road conditions were the cause of many accidents. Decreased traction on wet roads increases the distance required to stop vehicles and makes it difficult to maneuver safely. Since braking distances are longer on wet roads, it is necessary to maintain more distance with the vehicle ahead to prevent accidents.

Classification of road wetness and dryness is difficult due to the low performance of the current technology. In rain, the images captured by a camera are grainy or blurry, resulting in inaccurate results. Furthermore, there are not many available datasets to evaluate wetness. Therefore, we developed a device that captures road images and classifies road conditions in this study.

Amidst the continuous progress of technology, different methods have been developed that use artificial intelligence (AI) and machine learning (ML) [2]. Convolutional neural networks (CNNs) are an essential element of computer vision and machine learning applications. In this study, we used the MobileNet algorithm to classify road wetness using CCTV-captured images. Mask recursive CNN was used to classify road wetness

in Refs. [3–7]. In these studies, 12,190 images captured in various weather conditions were collected. A total of 1856 of these images were randomly subsampled and annotated for segmentation model training. However, the manual annotation of the images was a drawback in the segmentation model, while the discrepancies in the camera types and models used were another drawback. In other studies [8–12], road surface friction was estimated using road surface conditions without wetness estimation.

Wet road is a major concern due to the increasing number of accidents. To address this issue, a system for classifying road wetness is essential. MobileNet and mask R-CNN were used to determine road surface wetness using water film height measurement. Roads have different characteristics depending on their type, color, and material. Therefore, the wetness of roads can be estimated by processing and classifying these characteristics [13–15]. SqueezeNet and ENet can be integrated to accurately classify road wetness as SqueezeNet detects the features of the asphalt roads which are segmented semantically by ENet.

The system developed in this study adopted Raspberry Pi 4 to classify road conditions (wet or dry) using SqueezeNet and ENet. The system captured images with Raspberry Pi camera module 3 and processed images using SqueezeNet and ENet for the categorization of road wetness. The accuracy of the system was estimated by a confusion matrix created using the gathered and created datasets. The system helps drivers avoid accidents on the road and informs road conditions. The system can also be used to analyze and classify road conditions for different purposes. The system can be extended to classify the types of materials, skid resistance, or roads. The system and models serve as a basis for research on image processing using AI. The dataset created in this study can also be used in future research with the addition of images containing potholes, cracks, and road markings.

2. Methodology

Figure 1 shows the research framework of this study. We gathered 1200 images of the road surface. The captured images were classified using SqueezeNet to classify the wet and dry surfaces. The fire module was implemented in the squeeze layer to reduce the dimension to 1×1 and segment the gathered images. The images were then processed by the expand layer, increasing the depth of the network. The expand layer filtered the gathered images using 1×1 and 3×3 filters. The extracted features were fed to ENet for semantic segmentation. ENet segmented images at the pixel level, isolating the road regions from the surrounding areas. PyTorch 2.2.1 processed the data and displayed the outputs. The confusion matrix was created to evaluate the accuracy of the system's classification. The result of the classification was displayed on an OLED LCD. The images were collected by the Raspberry Pi camera module. The deep learning models classified road surface and wetness successfully.

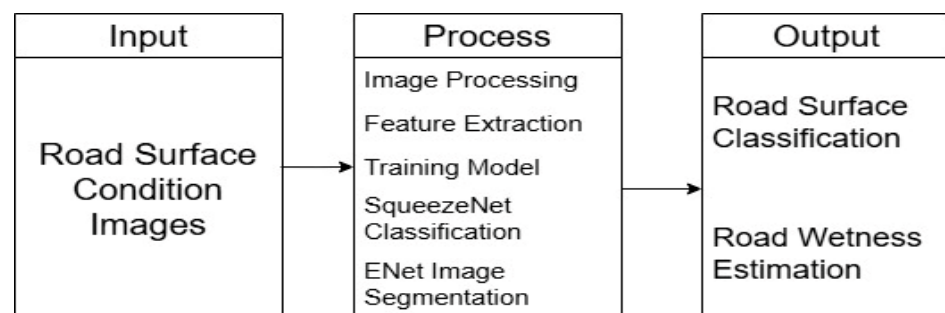


Figure 1. Research framework.

2.1. Hardware Development

Figure 2 shows the hardware of the developed system. The system consisted of Raspberry Pi 4, Raspberry Pi camera module 3, an SD Card, OLED, and a power source. As the system's microcontroller, Raspberry Pi 4 processed the inputs and outputs of the system. Raspberry Pi camera module 3 was connected to Raspberry Pi 4 for data collection. The camera module also captured images for classification. The SD card stored the operating algorithms, and an OLED display showed the results of wetness classification and estimation.

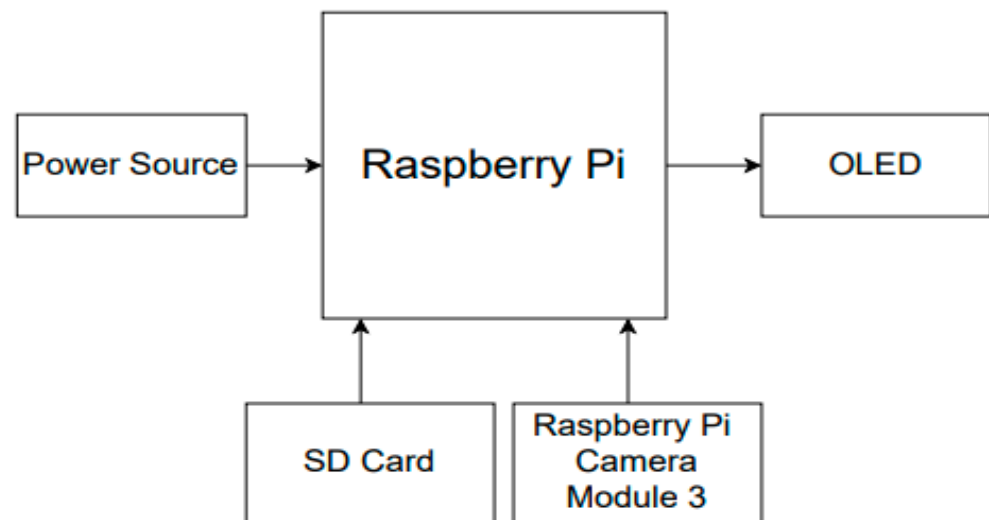


Figure 2. Hardware components of developed system.

2.2. Software

Figure 3 shows the software development process of the system. The process consisted of five modules: `imagePreprocess()`, `SqueezeNet()`, `ENet()`, `road surface classification RSC()`, and `road wetness estimation RWE()`. Each module included important features for identifying the type of road surface and determining wetness. The captured images were stored in the SD card to compose the database of the system. The images were resized into a fixed input state. The SqueezeNet model normalized the pixel value of the image to 1 to maintain the consistency of the images. The normalized images were classified by the SqueezeNet model to determine wetness. The extracted features were fed into ENet for semantic segmentation. The ENet model generated segmentation maps at the pixel level to effectively distinguish the road from the surrounding background. The deep learning models were trained to classify road surfaces and estimate road wetness. Residual shuffle convolution (RSC) and real-world evidence (RWE) processed classified images. The images were then categorized.

SqueezeNet detected features related to road surface conditions. Color, texture, and reflectivity were identified and saved for the next function. ENet estimated road wetness. The RSC module output road surface classification results after it detected road surface conditions based on the features. The RWE module managed the road wetness estimation. The wetness in the identified area was indicated.

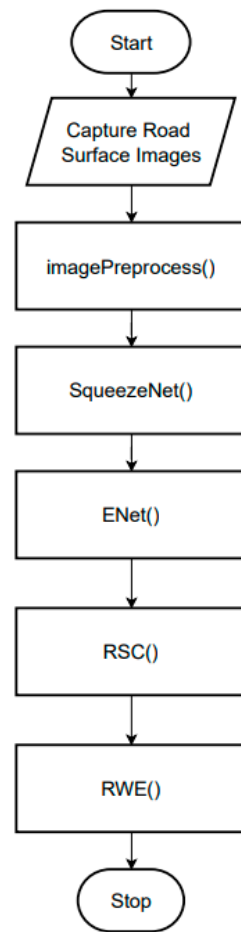


Figure 3. Software operation process in system.

2.3. Experimental Setup

Figure 4 shows the experimental setup of the system. The system was trained to classify road surface conditions and wetness using datasets. The camera module acquired the images of the road at 30 m. Wetness was estimated in percentage and was classified into dry, wet, damp, or flooded statuses. The dry status showed a wetness of 0%.



Figure 4. Experimental setup.

3. Results and Discussion

3.1. Data Gathering

After classifying the road surface condition as wet or dry, the system estimated wetness and displayed the result with the category. We gathered 1200 images with 300 images in dry, damp, wet, and very wet categories from the Internet. The road surface conditions were wet or dry. We constructed a dataset with images of roads from reliable sources (Table 1).

Table 1. Road surface condition dataset.

Road Surface Condition	Number of Images
Dry	300
Damp	300
Wet	300
Very wet	300

3.2. Statistical Analysis

The confusion matrix was used to estimate the accuracy of the system (Table 2). The SqueezeNet model accurately predicted 9 out of 10 for the dry category and 9 out of 10 for the wet category. The ENet model accurately predicted five out of seven for the damp category, seven out of seven for the wet category, and seven out of seven for the very wet category. A total of 21 test data points were used (Table 3).

Table 2. Confusion matrix for road surface condition classification.

		Actual		Total
		Dry	Wet	
Predicted	Dry	9	1	10
	Wet	1	9	10
Total		10	10	20

Table 3. Confusion matrix for road surface wetness estimation classification.

		Actual			Total
		Damp	Wet	Very wet	
Predicted	Damp	5	2	0	7
	Wet	0	7	0	7
	Very wet	0	0	7	7
Total		5	9	7	21

The true positive values represent the actual positive outputs. The rest are either false positives or negatives. Upon completion of the confusion matrix, accuracy was determined using (1) and (2).

$$Accuracy\ Rate\ (2 \times 2) = \frac{\sum_{n=1}^2 Ann}{\sum_{j=1}^2 Aij} \quad (1)$$

$$Accuracy\ Rate\ (3 \times 3) = \frac{\sum_{n=1}^3 Ann}{\sum_{j=1}^3 Aij} \quad (2)$$

Accuracy presents how often the system predicts the outcome correctly. True positive (TP) is the number of predicted values matching the actual values, and true negative (TN) is the frequency of the predicted negative values matching the actual negative values. False positive (FP) is the frequency of the algorithm incorrectly predicting negative numbers as positives, and false negative (FN) is the frequency of predicting positives matching the actual negatives. A summary of results for road wetness estimation (RWE) is shown in Table 4. The ENet model showed an accuracy of 71.43% for the damp category and 100% for the wet and very wet categories. The overall accuracy was 90.48%.

Table 4. Results of RSC.

Summary of Results		
Actual Values		Expected Values
Accuracy Rate (Dry and Wet)	90%	95%
Total Accuracy Rate	90%	95%

The results for road surface condition (RSC) are shown in Table 5. The SqueezeNet model showed an accuracy rate of 90% for the dry and wet categories. The accuracy was 90%.

Table 5. Results of RWE.

Summary of Results		
Actual Values		Expected Values
Accuracy Rate (Damp)	71.43%	95%
Accuracy Rate (Wet and Very Wet)	100%	95%
Total Accuracy Rate	90.48%	95%

4. Conclusions and Recommendation

We developed a system for road surface classification and wetness estimation using deep learning models, specifically the SqueezeNet and ENet models. After the implementation and testing of the system with Raspberry Pi 4 and camera module 3, the system accurately determined the road surface condition (dry or wet) and road wetness (damp, wet, or very wet). The SqueezeNet model achieved 90% accuracy, while the ENet model showed an accuracy of 90.48%. For the advancement of the system, the SqueezeNet and ENet models need to be further trained. More data must be added to the dataset, and the quality of the data needs to be improved. The data for training must be preprocessed to correctly classify the road conditions. Real-time inference of the SqueezeNet and ENet models helps the system determine the road surface condition and road wetness more effectively.

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