Road Surface Material Recognition from Dashboard Cameras

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Abstract. The recognition of road surface materials has significant implications for applications like enhanced navigation, traction and stability, predictive maintenance, safety considerations, transportation and infrastructure management, and autonomous driving. In this paper, we aim to accurately identify various materials used in road surfaces, including asphalt, bricks, cobblestone, gravel, among others. To this end, we collected a comprehensive image dataset acquired from dashboard cameras. Each image is annotated with a corresponding surface material groundtruth. Following the data collection, we employed diffusion methods to augment the training data for all surface material classes. Then, we propose a segmentation-classification framework which isolates the road surfaces from surrounding contexts such as buildings, vehicles, and pedestrians. Next, we introduce the road surface sample extraction from the segmentation results. We conducted experiments with various deep-learning models. The experimental results demonstrate that our proposed framework can recognize road surface materials with a high accuracy rate.

Keywords: Road surface material · dash cams · image processing · image segmentation · deep learning

1 Introduction

Road surfaces play a crucial role in transportation infrastructure by facilitating the smooth flow of vehicles. The materials used in building roads play a significant role in determining their quality and durability. Precisely recognizing these substances is essential for preserving, restoring, and organizing transportation systems. Material surface recognition of roads is also important in the operation of autonomous vehicles (AVs). For example, AVs can optimize navigation by identifying road materials like asphalt, soil, or gravel, allowing them to adjust speed and path for better performance and safety. Different surfaces offer varying traction and stability, enabling AVs to adapt driving techniques, especially in adverse weather. Recognizing surface materials helps forecast maintenance, as sensors detect road wear, enabling proactive repairs. Precise surface identification aids localization and mapping, enhancing AVs' positional accuracy, especially in GPS-limited or complex urban areas. Also, identifying materials also mitigates

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safety risks from surfaces prone to accidents during braking or cornering. Additionally, AVs can boost energy efficiency by adjusting tire pressure or speed based on surface type. There have been some works in literature [1–5] attempting to tackle this road surface recognition problem. However, these works did not focus on the dashboard cameras. In addition, they only focus on using the existing classifiers for the task.

In this paper, we focus on recognizing different types of road surface materials, ranging from conventional materials such as asphalt, bricks, and soil to less popular choices like cobblestone, and gravel from the perspective of dashboard cameras (dashcams). To this end, we first collect an image dataset of road materials from dashcams. The data collection phase was approached comprehensively by extracting frames from dashcams. This multifaceted strategy ensured the acquisition of a diverse and representative dataset, which is critical for the subsequent analysis and modeling phases of the research. Regarding the computational framework, we propose a segmentation-classification model along with road surface sample extraction for better recognition.

The remainder of this paper is organized as follows. Section 2 reviews the related work. Section 3 and Sect. 4 introduce the collected dataset and the computational framework, respectively. Section 5 presents the experimental results. Finally, Sect. 6 concludes the paper and paves the way to the future work.

2 Related Work

There exist many works of recognizing road surface materials and anomalies using deep learning in literature. Nolte *et al.* [1] utilized deep convolutional neural networks (CNNs) for road surface classification, while Cheng *et al.* [2] employed deep learning techniques to classify road surface conditions. Similarly, Balcerek *et al.* [3] utilized CNNs for road surface classification, demonstrating the effectiveness of these models. Rateke *et al.* [4] explored road surface classification with images from low-cost cameras. Meanwhile, Tang and Breckon [5] focused on automatic road environment classification, providing insights into the use of machine learning for surface identification. Zhao *et al.* [6] implemented a road surface classifier aimed at vehicle driving assistance, incorporating datasets, models, and deployment strategies.

In another work, Deepa and Sivasangari [7] proposed a hybrid deep learning framework for detecting and classifying road damages, highlighting the importance of multimodal approaches. Agrawal et al. [8] combined road surface classification with pothole detection using deep learning, illustrating practical applications. Menegazzo and Von Wangenheim [9] compared classical and deep learning approaches for multi-contextual real-world scenarios using inertial sensors for surface type classification. Paswan *et al.* [10] introduced a framework for road scene and surface segmentation in unstructured environments using computer vision and deep learning. Xu *et al.* [11] and Zhang *et al.* [12] focused on road extraction from high-resolution remote sensing imagery, employing deep learning techniques like deep residual U-net. Wang *et al.* [13] proposed a neural-dynamic framework combining deep learning and finite state machines for road network extraction. Park *et al.* [14] utilized a deep ensemble network with sensor feature selection for road surface classification, while Lee *et al.* [15] implemented intelligent tire sensor-based real-time classification using artificial neural networks.

Fig. 1. Examples of 8 road surface material classes, namely, asphalt, bricks, cobblestone, gravel, puddles, red soil, soil, and wet asphalt. (Color figure online)

From the surface material recognition, Doğan and Ergen [16] introduced a mobile CNN-based approach for pixel-wise road surface crack detection. Torbaghan *et al.* [17] and Bhat et al. [18] reviewed road crack detection techniques, emphasizing automated detection using ground-penetrating radar and various machine learning methods. Fan *et al.* [19] used encoder-decoder architecture for automatic crack detection on pavements. Chen and He [20] developed a novel U-shaped encoder-decoder network with an attention mechanism for pixel-level crack detection and evaluation. Dhiman and Klette [21] tackled pothole detection using computer vision and learning, while Alfarrarjeh *et al.* [22] applied deep learning for road damage detection from smartphone images. Meanwhile, Martinez-Ríos *et al.* [23] reviewed vibration-based techniques for detecting and classifying road surface anomalies. Ozoglu and Gökgöz [24] applied CNN methods based on road vibration data for pothole detection. Rateke and Von Wangenheim [25] extended their research to differentiate road surfaces considering surface damages. In another work, Zhuravlev and Aksyonov [26] compared contour detection methods for road surface damage, and Abbas and Ismael [27] automated pavement distress detection using image processing techniques. Ayala *et al.* [28] enhanced building footprint and road detection in high-resolution satellite imagery with deep learning. Kim et al. [29] focused on deep learning-based underground object detection for urban road pavement, providing insights into subsurface anomalies. Chen *et al.* [30] developed a road damage detection algorithm based on an object detection network, showcasing advanced methodologies in surface anomaly detection.

3 Dataset Collection

We encounter the first challenge regarding the data for model training and evaluation, particularly in sourcing a diverse range of dashcam images representing different types of road surfaces. The challenge poses a legitimate need to construct a new dataset for this research problem. Therefore, we first build a dataset of dash cams. In particular, we collected the images for 8 classes, namely, asphalt, bricks, cobblestone, gravel, puddles, red soil, soil, and wet asphalt. During the dataset construction, we meticulously collected over 100 images for each class, ensuring a comprehensive representation of each surface type. These images were sourced from multiple dashcam videos, including many from YouTube videos. This approach not only expanded the variety of conditions captured but also enhanced the dataset's relevance and applicability to real-world situations. Figure 1 shows examples of different surface material classes. Table 1 shows the number of images for each class for training, as well as testing. The strategic compilation of this dataset facilitates our research, providing a solid foundation for training and benchmarking models aimed at accurately identifying and classifying different road surfaces.

Table 1. The statistics of the collected dataset for road surface material recognition.

Class	Training	Testing	Total
Asphalt	187	15	202
Bricks	226	20	246
Cobblestone	187	15	202
Gravel	175	15	190
Puddles	184	25	209
Red Soil	222	30	252
Soil	213	35	248
Wet Asphalt	177	15	192
Total	**1571**	**170**	**1741**

4 Computational Framework

The deep convolutional neural network (CNN) models such as LeNet [31], AlexNet [32], VGG [33], ResNet [34], DenseNet [35] are popular for classification task. In this work, we further extend the deep CNN with the side information such as the segmentation results, road surface sampling, and data augmentation with diffusion [36]. The details are listed below.

4.1 Segmentation-Classification Model

Instead of directly feeding the input image into the Convolutional Neural Network (CNN) model, we first perform the image segmentation [37] on the input image. The segmentation process divides the image into different semantic classes such as sky, tree, road, grass, water, building, and mountain. The primary objective of image segmentation is to assign a label to every pixel in the image, which effectively delineates the boundaries and identifies various elements within the scene. By leveraging the results of image segmentation, we can obtain detailed information about the different regions within the image. Specifically, we use the segmentation results as side information to isolate and separate the road-only area from the rest of the image. This isolated road-only area is then extracted and prepared for further processing. Next, we feed this road-only area into a deep CNN for classification purposes. This two-step process, involving initial segmentation followed by focused classification, ensures that CNN receives input that is more relevant and context-specific, potentially improving the accuracy and efficiency of the classification task. Figure 2 illustrates the complete flowchart of our segmentation-classification model, highlighting each step from initial image segmentation to the final classification of the road-only area. This approach not only enhances the model's performance but also provides a more structured and organized way to handle complex image data.

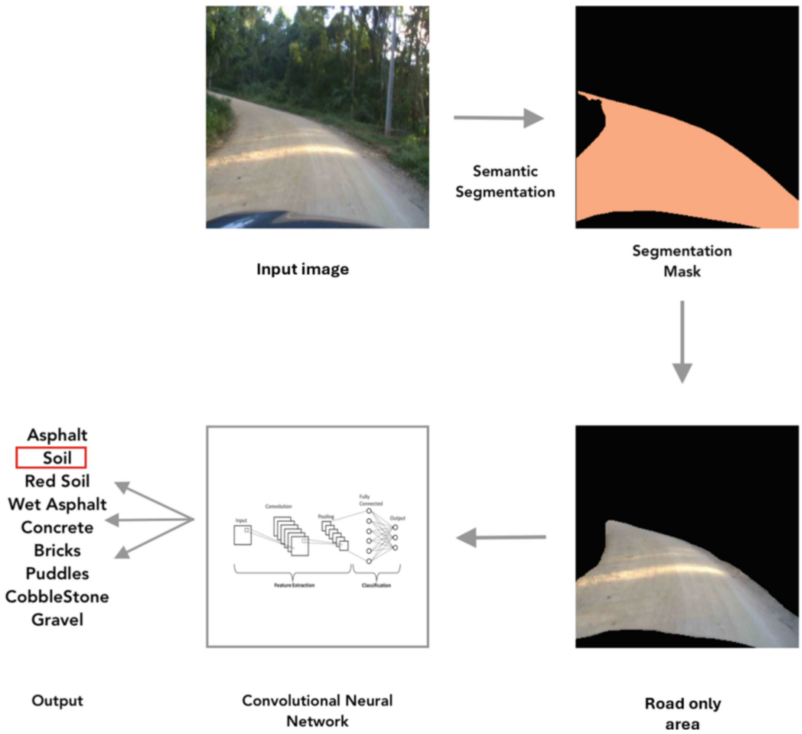

Fig. 2. The flowchart of the segmentation-classification model for the road surface material recognition.

4.2 Road Surface Sample Extraction

Inspired by the road surface sample extraction in civil engineering which collects samples from road surfaces to analyze their material, composition, structure, and condition, we further extract the road surface in the image for a better classification. In particular, we compute the image integral [38] of the segmentation mask. Note that the integral image or summed-area table is a data structure that allows for quick and efficient calculation of the sum of pixel values within a rectangular region of an image. It speeds up computations in tasks like object detection and feature extraction by enabling constant-time area summations. Then, we extract the square block which contains the most pixels. Figure 3 shows examples of the road surface samples extracted from input images by using segmentation mask and image integral. Then, we extract the corresponding block in the road image. Finally, we feed the extracted square block into the CNN model for the classification.

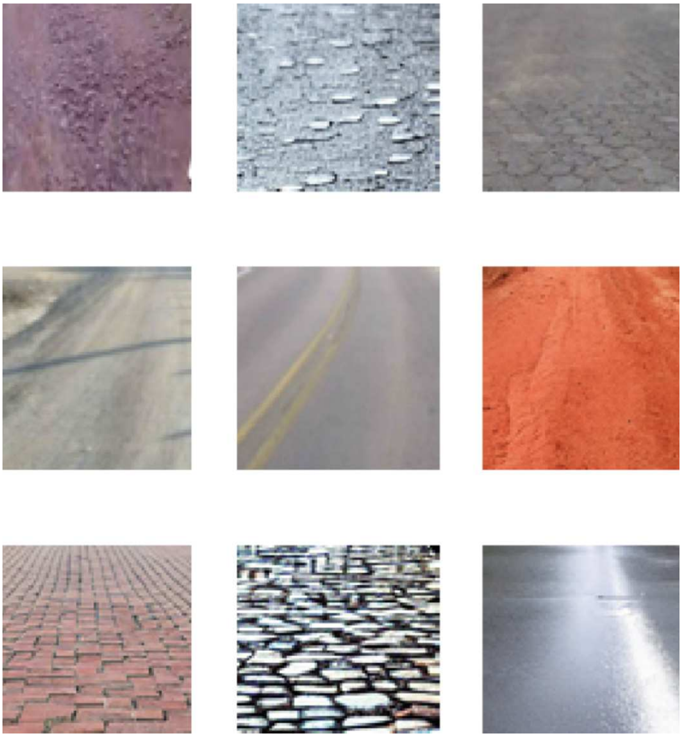

Fig. 3. Road surface sample was taken from the images by using the segmentation mask and the image integral.

4.3 Data Augmentation with Diffusion

In order to improve the model training, we further augment the training data with diffusion [36]. Specifically, we adopt innovative methodologies involving diffusion and prompts to augment our dataset with images that closely resemble those obtained directly from the internet. This approach aims to enhance the diversity and realism of our dataset, consequently improving the robustness and generalization capabilities of our machine-learning models. In short, diffusion is an effective technique in image generation that involves iteratively applying noise to an image while gradually reducing the noise level. This process simulates the gradual spread or diffusion of information throughout an image, resulting in visually realistic yet novel variations. By providing prompts related to road scenes, landscapes, or other relevant contexts, we steer the generation process toward producing images that align with our dataset's target domain. By combining diffusion and prompts methodologies, we systematically generate synthetic images that closely mimic the characteristics and diversity of raw internet-acquired images. These augmented images complement our existing dataset, enriching it with additional variations and complexities that may not be adequately represented in the original dataset alone (Fig. 4).

Fig. 4. Some augmented data generated by using diffusion for classifying road surface materials.

5 Experiments

5.1 Implementation and Experimental Settings

For the implementation, we consider various CNN models such as ResNet101 [34], VGG16 [33], VGG19 [33], DenseNet169 [35], DenseNet121 [35], DenseNet201 [35], and InceptionV3 [39]. We set the input image size to 255 × 255 for all of the models.

Regarding the image integral, we opt to the size of 80×80 for the square block. We utilize the fully convolutional network (FCN) [37] trained on SIFTFlow dataset [40] for image segmentation component. The experiments are conducted on the newly collected dataset as mentioned in Sect. 3. Regarding the performance metrics, we utilize the accuracy rate which is common for the classification task as in [41, 42].

Table 2. The experimental results with different settings. The best, second best, and third best are marked in **red**, *green*, ***blue***, respectively. Note that all of the methods utilize diffusion for data augmentation.

Model	Full Image	Segmentation-Classification	Road Surface Sample Extraction
ResNet101	52.35	57.06	57.65
VGG19	69.41	75.88	77.06
VGG16	74.71	76.47	80.59
DenseNet169	77.06	78.24	81.18
DenseNet121	78.24	81.76	***82.94***
DenseNet201	76.47	*84.12*	**85.88**
InceptionV3	78.24	79.41	80.59

5.2 Experimental Results

Table 2 shows the results of different models on the collected dataset. We report the results of the full input image, segmentation-classification model, and road surface sample extraction. Note that all the models use the data augmented from the diffusion. The results clearly demonstrate a notable enhancement in accuracy when utilizing the segmentation results to isolate the road-only areas. Across all models, training on isolated roads yielded substantially higher accuracy compared to training on data containing background details. This highlights the effectiveness of isolating roads from background noise before training the models. By focusing solely on the road surfaces, the models were able to achieve better performance in accurately identifying and classifying road surfaces. This emphasizes the importance of preprocessing techniques such as segmentation in enhancing the quality of training data and subsequently improving model performance. DenseNet201 achieves the best results over baselines in both segmentation-classification model and road surface sample extraction, i.e., 84.12 and 85.55. We can observe a huge gain from the full image to road surface sample extraction, i.e., 76.47 vs. 85.55. This clearly demonstrates the effectiveness of the proposed method.

We take a closer look at the performance of DenseNet201 by examining its confusion matrix (as shown in Fig. 5). The model works extremely well in various classes such as soil, puddles, or red soil. Meanwhile, there exist some classes that the model struggles to, for example, asphalt or brick. This absolutely attracts our attention to these classes for future work.

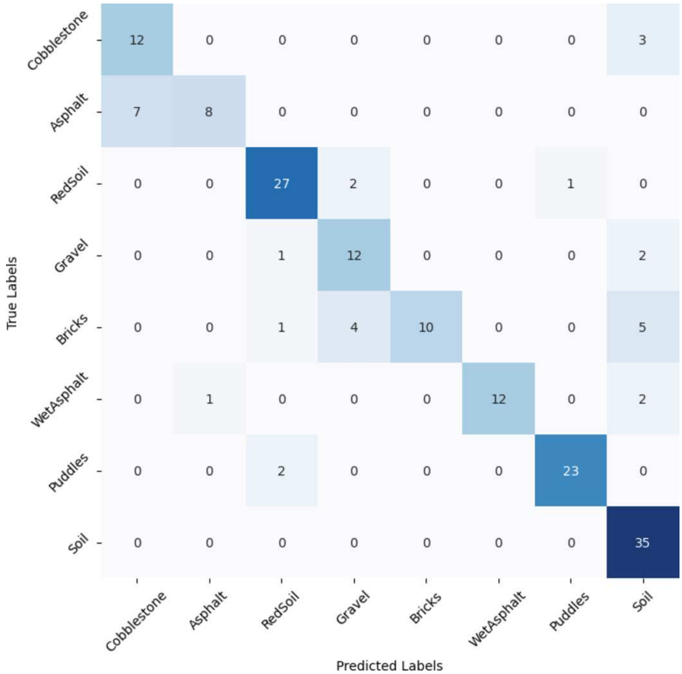

Fig. 5. The confusion matrix of DenseNet201 on the benchmark dataset. The darker blue, the better classification result. (Color figure online)

6 Conclusion and Future Work

In this paper, we tackle the task of accurately recognizing various road surface materials such as asphalt, bricks, cobblestone, gravel, among others. By constructing a comprehensive image dataset from dashcam videos and annotating each image with the corresponding surface material groundtruth, we introduce a solid foundation for this research area. Our proposed segmentation-classification framework effectively isolates road surfaces from surrounding contexts, enhancing material identification precision. In addition, the road surface sample extraction shows good performance. Experimental results from various deep-learning models validate our framework's efficacy, demonstrating its ability to recognize road surface materials with high accuracy. These findings highlight the potential of our approach for enhanced navigation, traction and stability, predictive maintenance, safety considerations, transportation and infrastructure management, and autonomous driving.

In the future, we focus on enhancing road surface material identification by expanding the dataset to include a broader range of materials and diverse environmental conditions, such as different weather and lighting scenarios. We plan to explore unsupervised and semi-supervised learning techniques to reduce dependency on annotated data. In addition, we are interested in collecting videos instead of video frames which requires more storage and more computational cost.

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