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ROAD SURFACE CLASSIFICATION USING RESNET

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Abstract-An essential but unfinished challenge is the creation of a surface recognition system for automobiles. In this research, we take a fresh look at surface categorization by examining photographs of actual road surfaces. High surface classification accuracy is achieved by using the suggested experimental approach in conjunction with a deep neural network. This study contains original work for road surface categorization using Deep Learning architecture. The importance of studying the vehicle's status has grown as technologies like the advanced driver assistance system (ADAS) and autonomous driving have progressed. However, studies on how to categorize road surfaces have not been done as of yet. If the control system is capable of classifying and recognizing road surfaces, it can verify the data from other sensors and make a more confident decision. That's why it's so important to categorize the road surfaces.

Keywords:Deep learning architecture, Advanced driver assistance(ADAS), Autonomous driving technologies.

1. INTRODUCTION

The development of autonomous vehicle (AV) technology has been successful during the last several years. AV is being considered by major corporations as a means to lessen the number of traffic-related deaths and injuries. Researchers in Europe found that motorist mistake was the leading cause of traffic accidents. This causes over 25,000 fatalities annually in Europe due to traffic accidents. Financial losses are substantial even in the event of minor collisions. This highlights the significance of av as a means to counteract human mistake and improve road user safety. Although there has been significant progress in AV development in recent years, there are still several unresolved issues, including the creation of a surface identification (surface ID) system. This system should remotely categorize the road surfaces and warn the driver or av computer of potentially hazardous road surfaces, ice, standing water, or changes in the road path, allowing and the vehicle to remain safely under control as it transitions from one surface to another, thereby minimizing costly damage, avoiding injury, and potentially saving lives. One of the most important aspects of offering autonomous driving is the ability for vehicles to automatically adjust their speed based on the terrain.

Keeping tabs on the state of the roads is crucial for transportation departments worldwide. The quality of maintenance services given by contractors across various maintenance yards may be assessed, alternative treatment techniques compared, and the demand for maintenance services determined using the data collected on the state of the roads. Travelers and drivers may benefit from real-time data on road surface conditions by making more informed choices about when, where, and how to get from one place to another.

Road weather information systems (RWIS) placed at strategic sites or eye inspection and manual recording by maintenance workers are the two most common methods now used for monitoring the state of roads. One is restricted in its capacity to cover a certain area, while the other lacks impartiality, reproducibility, specifics, and timeliness.

In this study, we propose a method to monitor road conditions using Google Street View photos collected by inexpensive video and still cameras installed on non-dedicated vehicles, such as public transportation or police cars. The goal of this endeavour is to develop a method for objective, repeatable, and cheaply collecting data on road surface covering, which can then be used for widespread applications.

The purpose of this work is to make a first step in creating an image-based system that may be used to differentiate between six distinct road types (asphalt, uneven, rocky, mud, river, and gravel). In this work, we take a look at the state of the art in terms of image-based road condition categorization methods, present the fundamental notion underlying our suggested system, and talk about our first findings and potential next steps in this field.

1.1 OBJECTIVES:

The paper's main requirements for use are detailed below:

1. A capability to identify the road surface.
2. Find different kinds of roads
3. Recognize the road as a separate element from the image's background.
4. Accurate data.

2. PROPOSED SYSTEM

Finding sufficient amounts of high-quality, human-annotated training data may be difficult when teaching neural networks. Class imbalance, where certain classes are over-represented (majority classes) and others are under-represented (minority classes), presents a difficulty when training neural networks for classification tasks. Classification performance might suffer greatly if certain classes predominate in the training set or if other classes are only represented by a few of examples. This has the following ramifications for the use of deep convolutional networks in the task of road surface classification: There is not a dedicated dataset for road surface classification, unlike the several that exist for general image classification (ImageNet) or autonomous driving in general (KITTI). Therefore, we have collected road surface photos from the web and trained a ResNet model to assign several class labels to each image.

Multiple decades of mass production of automobiles have seen the incorporation of systems for dynamic control. Estimating the coefficient of friction between the tyres and the road, which represents the maximum adhesive force between the tyres and the road, is a key difficulty for the development of effective control algorithms. The quality of the road surface has a significant influence on the maximum transmittable drive or braking force, the precise amount of which relies on a number of parameters including the tyre and road temperatures as well as the tire's composition. As a result, there is a lot of talk on how to accurately estimate the friction coefficient in the subject of vehicle dynamics. Many of the proposed methods are reactive in nature, making use of, for instance, the currently observed dynamics of the vehicle to estimate the friction coefficient in observer-based systems. Under-vehicle sensors (microphones, radar, optical sensors) may be employed as an alternative to reactive estimating in order to capture the road surface underneath the car. While such reactive techniques have been proved to improve control performance, predictive approaches offer even more advantages for control performance, since a look-ahead estimate permits an early adaption of control algorithms to impending road circumstances. Understanding the road ahead of an autonomous vehicle is useful not only for its control, but also for its trajectory planning, since it enables the vehicle to adopt planning methods, such as slowing down or swerving to avoid rough or uneven road portions. Camera photos give high-resolution texture information, while LIDAR and RADAR sensors are able to identify river surfaces owing to their varying reflectance. Texture data may be used to spot riverbeds, but also to tell the difference between gravel and asphalt roadways. The new data has already been used to make educated guesses about the friction coefficient of roads. It looks interesting to employ a CNN-based strategy for surface categorization since Deep Convolutional Neural Networks (CNNs) have been successfully used to numerous classification problems, including with applications in the area of autonomous driving. However, the effectiveness is highly dependent on the structure of the training data. Most existing data sets were captured under dry, varied terrain conditions, whereas rainy circumstances yielded mud and river photos. In this study, we demonstrate ResNet-based convolutional network designs for differentiating between six types of road surfaces using this dataset.

As a result, there's a need for a system that can instantly categorize the road conditions everywhere (e.g., asphalt, rocky, mud, uneven, gravel, and river). ResNet techniques will be used to do the categorization automatically. In particular, a straightforward method of form: label will be used instead of the traditional feature-extraction-based method. We tackle the subject of labeling traffic situations in the wild. Information is drawn from footage captured by cameras installed in moving vehicles. When being trained, each frame is assigned a label from a set of six categories (asphalt, rocky, mud, uneven, gravel and river). Our ability to collect photographs belonging to these categories informed our decision on which classes to use as the outputs for our models. Training and testing under dynamic conditions is a major part of our research. That's why we think it's important to know about image processing and road types. In our study, we are using otsu Segmentation, a method through which 3D pictures are flattened into 2D representations. It is unnecessary to do training and testing since the photos we used came directly from Google and were therefore fully taught.

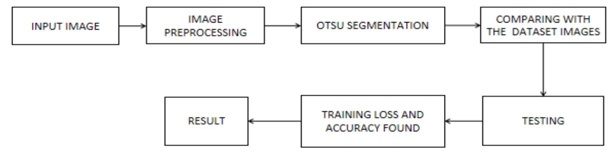

Fig2.1: System Architecture

3. RESULTS

Figure 3.1: The Image of The Road To Be Tested

In order to categorize the kind of road shown in the test image, we have imported the image from Google's dataset and used it to create our own dataset.

Figure 3.2: The Image Of The Road To Which Otsu segmentation Is Done

To better detect any objects in the test image, it is first transformed to a grayscale or black-and-white version.

Figure 3.3: This Is The Dataset To Which We Compare The Image

To determine the classification of the road, these pictures are extracted from the Google database and organized into a special category.

Figure 3.4: The Taken Image Is Plotted Against The Database Classes

The tested image is compared with dimensions of the images from the database/unique class and are labeled with the class names

```
Starting training..
Starting epoch 1/3
====================
Evaluating at step 0
Val loss: 1.9966, Acc: 0.0000
Accuracy::: 0.0
Training loss: 0.1250
Starting epoch 2/3
====================
Evaluating at step 0
Val loss: 1.9338, Acc: 0.3333
Accuracy::: 0.3333333333333333
Training loss: 0.1190
Starting epoch 3/3
====================
Evaluating at step 0
Val loss: 1.8364, Acc: 0.3333
Accuracy::: 0.3333333333333333
Training loss: 0.0783
Result....
```

Figure 3.5: Checking The Code To Figure Out The Accuracy And Training Loss

We can notice an improvement in accuracy and a reduction in training loss once the code has been run.

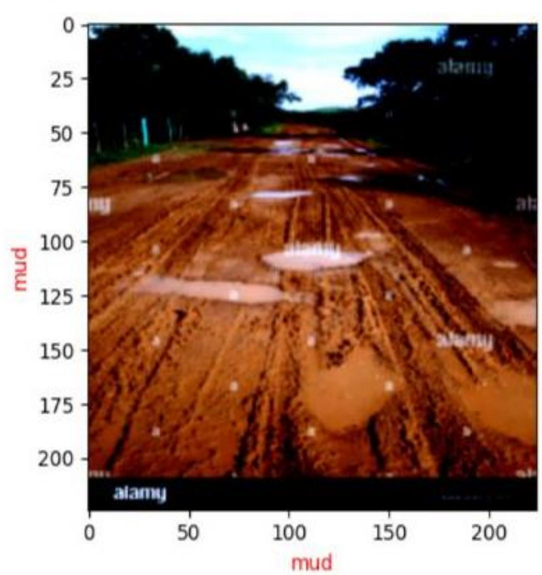

Figure 3.6: The Image That Is Of The "Mud" Road Type

After applying several feature improvement and extraction methods to the examined picture, it was determined to be of the "MUD" type road.

4. CONCLUSION

To forecast the road friction coefficient, we introduced a ResNet-based method for classifying road surfaces. In fact, the trained network models can tell the difference between six distinct surface labels. ResNet's overall classification accuracy was increased by 4% and confusion when discriminating between the roads was minimized by using photos from Google search results for minority classes in addition to data from publicly accessible datasets for autonomous driving. When it comes to prediction efficiency, our method has the potential to be a foundational component of an autonomous driving system (self-driving automobiles).

FUTURE SCOPE

By expanding the number of layers in the road network, we may achieve significant improvements in both accuracy and loss in training over preexisting methods. If we want faster results, we may also experiment with alternative CNN and Deep Learning methods (i.e., time decrease). In addition, we may tweak the program such that immediate assistance is sent to the traveler/driver in the event of an accident. It is possible to create the code for automated recommendation in addition to the current road type identification.

REFERENCES

[1] A. Valada and W. Burgard, "Deep spatiotemporal models for robust proprioceptive terrain classification," The International Journal of Robotics Research, vol. 36, pp. 1521–1539, 13-14 2017.

[2] K. Han, E. Lee, M. Choi, and S. B. Choi, "Adaptive Scheme for the Real-Time Estimation of Tire-Road Friction Coefficient and Vehicle Velocity," IEEE/ASME Transactions on Mechatronics, vol. 22, no. 4, pp. 1508–1518, 2017.

[3] F. Holzmann, M. Bellino, R. Siegwart, and H. Bubb, "Predictive estimation of the road-tire friction coefficient," in 2006 IEEE Intern. Conference on Control Applications, 2006, pp. 885–890.

[4] R. Omer and L. Fu, "An automatic image recognition system for winter road surface condition classification," in 2010 IEEE Intern. Conference on Intelligent Transportation Systems (ITSC), 2010, pp. 1375–1379.

[5] Y. Qian, E. J. Almazan, and J. H. Elder, "Evaluating features and classifiers for road weather condition analysis," in 2016 IEEE Intern. Conference on Image Processing (ICIP), 2016, pp. 4403–4407.

[6] A. Geiger, P. Lenz, C. Stiller, and R. Urtasun, "Vision meets Robotics: The KITTI Dataset," International Journal of Robotics Research (IJRR), vol. 32, no. 11, pp. 1231–1237, 2013.

[7] W. Maddern, G. Pascoe, C. Linegar, and P. Newman, "1 Year, 1000km: The Oxford RobotCar Dataset," The International Journal of Robotics Research (IJRR), vol. 36, no. 1, pp. 3–15, 2017.

[8] T. Nothdurft, P. Hecker, S. Ohl, F. Saust, M. Maurer, A. Reschka, and J. R. Bohmer, "Stadtpilot: First Fully Autonomous Test Drives ¨ in Urban Traffic," 2011 IEEE Intern. Conference on Intelligent Transportation Systems (ITSC), 2011, pp. 919–924.

[9] A. Giusti, J. Guzzi, D. C. Ciresan, F.-L. He, J. P. Rodriguez, F. Fontana, M. Faessler, C. Forster, J. Schmidhuber, G. D. Caro, D. Scaramuzza, and L. M. Gambardella, "A Machine Learning Approach to Visual Perception of Forest Trails for Mobile Robots," IEEE Robotics and Automation Letters, vol. 1, no. 2, pp. 661–667, 2016.

[10] M. Smith, I. Baldwin, W. Churchill, R. Paul, and P. Newman, "The new college vision and laser data set," The International Journal of Robotics Research, vol. 28, no. 5, pp. 595–599, 2009.

[11] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in 2016 IEEE Intern. Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770–778.

[12] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in 2016 IEEE Intern. Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 2818–2826.

[13] S. Khaleghian, A. Emami, and S. Taheri, "A technical survey on tireroad friction estimation," Friction, vol. 5, no. 2, pp. 123–146, 2017.

[14] M. Varma and A. Zisserman, "A Statistical Approach to Material Classification Using Image Patch Exemplars," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 31, no. 11, pp. 2032– 2047, 2009.

[15] H. Bay, T. Tuytelaars, and L. Van Gool, "SURF: Speeded Up Robust Features," in Computer Vision – ECCV 2006, A. Leonardis, H. Bischof, and A. Pinz, Eds., Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, pp. 404–417.

[16] M. Buda, A. Maki, and M. A. Mazurowski, "A systematic study of the class imbalance problem in convolutional neural networks," CoRR, vol. abs/1710.05381, 2017.

[17] J. Deng, W. Dong, R. Socher, L.-J. Li, Kai Li, and Li Fei-Fei, "ImageNet: A large-scale hierarchical image database," in 2009 IEEE Intern. Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, 2009, pp. 248–255.

[18] Z. Pezzementi, T. Tabor, P. Hu, J. K. Chang, D. Ramanan, C. Wellington, B. P. W. Babu, and H. Herman, "Comparing Apples and Oranges: Off-Road Pedestrian Detection on the NREC Agricultural Person-Detection Dataset," CoRR, vol. abs/1707.07169, 2017.

[19] J. Krause, B. Sapp, A. Howard, H. Zhou, A. Toshev, T. Duerig, J. Philbin, and L. Fei-Fei, "The Unreasonable Effectiveness of Noisy Data for Fine-Grained Recognition," in Computer Vision – ECCV 2016, B. Leibe, J. Matas, N. Sebe, and M. Welling, Eds., Cham: Springer International Publishing, 2016, pp. 301–320.

[20]] C. Sammut and G. I. Webb, *Encyclopedia of Machine Learning*. Boston, MA, USA: Springer, 2011.

[21] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. Imagenet: A large-scale hierarchical image database. In Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on, pages 248–255. IEEE, 2009.

[22] F. Feng, L. Fu, and M. S. Perchanok. Comparison of alternative models for road surface condition classifification. In TRB Annual Meeting, 2010.

[23] Y. Qian, E. J. Almazan, and J. H. Elder. Evaluating features and classififiers for road weather condition analysis. In Image Processing (ICIP), 2016 IEEE International Conference on, pages 4403–4407. IEEE, 2016.

[24] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov. Dropout:
A simple way to prevent neural networks from overfifitting. The Journal of Machine

Learning Research, 15(1):1929–1958, 2014.

[25] J. Deng, W. Dong, R. Socher, L.-J. Li, Kai Li, and Li Fei-Fei, "ImageNet: A large-scale hierarchical image database," in 2009 IEEE Intern. Conference on

Computer Vision andPattern Recognition *(CVPR)*, IEEE, 2009, pp. 248–255.

[26] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in 2016 IEEE Intern. Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770–778.