A Comparative Study on Road Surface State Assessment Using Transfer Learning Approach

Conference Paper · October 2022

DOI: 10.1109/ICCCNT54827.2022.9984393

5 authors, including:

Fahim Ur Rahman
Daffodil International University

Md. Tanvir Ahmed
Daffodil International University

Md Risfat Amin
Daffodil International University

Nusrat Nabi
Daffodil International University

A Comparative Study on Road Surface State Assessment Using Transfer Learning Approach

Fahim Ur Rahman
Dept. of CSE
Daffodil International University
Dhaka, Bangladesh
fahim15-13674@diu.edu.bd

Md. Tanvir Ahmed
Dept. of CSE
Daffodil International University
Dhaka, Bangladesh
tanvir15-13602@diu.edu.bd

Md Risfat Amin
Dept. of CSE
Daffodil International University
Dhaka, Bangladesh
risfat15-13488@diu.edu.bd

Nusrat Nabi
Dept. of CSE
Daffodil International University
Dhaka, Bangladesh
nusrat15-10524@diu.edu.bd

Mr. Md. Sazzadur Ahamed
Dept. of CSE
Daffodil International University
Dhaka, Bangladesh
sazzad.cse@diu.edu.bd

***Abstract*—Automatic detection of road surface condition and classified data storage is proposed using a customized VGG16 model. One of the primary concerns affecting safety in transportation is road surface distress. The first sign of an asphalt pavement's catastrophic collapse is a surface crack, which can later progress to become a pothole and incur expensive repairing costs. Conventional detection methods of road surface cracks or degradation that included manual checking by humans adds to additional time and resource cost which can be eradicated by replacing the monitoring system with an automated computer program that we are proposing in this study. A deep neural network that is trained on custom dataset collected manually by taking photos of roads to successfully detect smooth and cracked or damaged road surfaces is proposed on this domain. VGG16 with a custom input layer has been proven to achieve 97.52% accuracy in detection of both smooth and damaged surfaces which, compared to others, is much better than the other models. The classified images from the model can later be used by specific authorities trying to maintain the road infrastructures.**

***Keywords*—Road Surface, Transfer Learning, Computer Vision, VGG16, Custom Dataset**

I. Introduction

With the number of fatalities in accidents increasing, the question regarding the safety of the roadways is being highlighted. In fact, a startling increase in traffic accidents in the capital in recent years has caused serious worry among citizens from all aspects of society. Although the main culprit behind almost all of these devastating accidents is reckless and overspeed driving of the vehicles, some minor reasoning can also be proven to be the quality of road surfaces. Due to lack of proper maintenance and monitoring of important roads, over time the roads start to degrade and gradually reach a level when it is both risky and not usable for smooth transportations. Overall road infrastructure silently contributes significantly to maintaining road safety for vehicles. But, in want of proper maintenance, the infrastructure starts to collapse indicating negative impacts to the safety measures of roads. Maintaining smooth roads for an extended period of time becomes even more burdensome when it comes to allocating budgets for it as the accidents of the road alone causes around 50-70 billion in national loss every year according to Accident Research Institute of BUET [1]. Many of the initiatives from the authority including limiting overspeed driving, increasing public awareness and deploying more law enforcers on roads, everything gets ruined due to even a slightly damaged portion of road. Vehicles can safely drive at a safe speed but a sudden bump in the road or badly damaged road portions come in front, there is very little to do to avoid collisions or unexpected damage to passengers inside the vehicles. The United Nations along with the World Health Organization (WHO) have also agreed in the term that "unsafe roads" are among one of the major reasons behind road accidents [2]. Road infrastructures are one of such kinds that is meant to degrade over time. When the developed countries are not worried about wearing out road surfaces, underdeveloped and developing countries suffer the most when it comes to road quality degradations. This is because these countries undergo a hard time building roads properly, so it is easy to expect that the monitoring and maintenance of these roads will not be as good as one of the developed countries. As a result, roads keep getting damaged and full of potholes and the authorities cannot put enough effort and accommodate a proper budget for checking each and every road.

Multiple studies of identifying road damages and potholes have been conducted over the past few years using gyroscope sensors, accelerometer sensors of mobile phones etc. but in a real-life scenario, jerking from a phone which is detected by gyroscope sensors is not very optimistic. Rather, if we try to develop a system based on computer vision that can operate on its own, it seems to be more efficient in terms of valid detections. Also, various aspects of ML and DL techniques using multiple CNNs are also being implemented. We also analyzed some of the recent deep learning algorithms for efficiently detecting road surface conditions. Training a deep

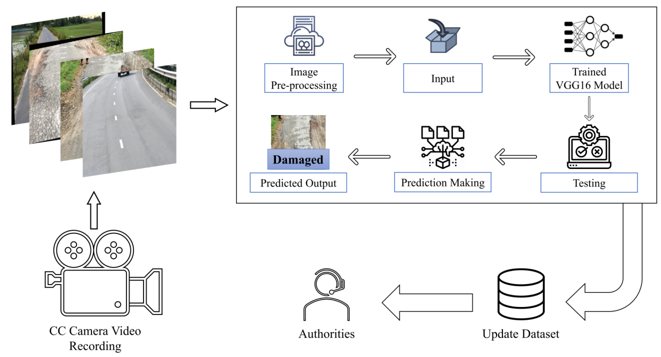

Fig. 1. Proposed System Architecture

neural network from scratch requires a tremendous amount of resources along with time. Instead, we can apply transfer learning techniques that opens the potential of using pre-trained models with custom tuning applied to the topmost layer. In our study, we have implemented several transfer learning models using the pre-trained version of DNNs over our custom-made dataset and classify multiple types of roads based on the predictions of the model. Then, the model with the highest achieved accuracy is proposed and the influences of using the model is analyzed after validating it over different road scenarios. The contributions of our study can be denoted as:

- The model that we propose through this paper can be used for detecting damaged surfaces of roads which are in need of urgent maintenance that indicates a reduction in maintenance cost.
- A dataset consisting of the local street of Dhaka, Bangladesh has been prepared that can also contribute to future studies.
- Our proposed model is expected to be able to classify even more classes of images once successfully trained with additional labeled image sets.

II. Literature Review

The main motivation that led us to collect dataset manually from open road scenarios and try to implement an automated road surface condition classifier was to ease the workflow of the authorities that are regulated to maintain these. As we are in an era of artificial intelligence, we can at least expect something from the point of view of a computer vision system that will blend in with the workflow of a directed authorities. Although we are not completely able to address the whole system through our work, the least our work can contribute to the concerned authorities can be proven over the upcoming times. In the context of a crowdsensing-based application, Braian et al.'s proposed deep learning approach allowed them to automatically identify the various types of road surfaces and distinguish potholes from destabilization caused by speed bumps or driver actions. They have suggested a method to separate stability events caused by potholes from stability events caused by other man-made structures or driver behavior. CNN outperformed other models achieving 98% accuracy on classifying two classes, potholes and no-potholes [3]. Combining training results of the Oxford RobotCar dataset and the KITTI dataset, an improved activation function of Gai-ReLU resulted in achieving a classification accuracy of 94.89% over five different categories of road surfaces. Their tests demonstrated that there was still room for improvement in terms of hyperparameters and structure for the proposed deep learning model based on an enhanced activation function [4]. To simulate the identification of the signs under the dirty damage scene, Zhang et al., 2019 chose to use the self-built road marking database and the data expansion method. For datasets they used the KITTI Dataset, Road Marking database and Baidu apollo database. The SSD/FSSD had faster speeds for fixed input sizes of 300*300, but had a significant impact on small target detection of large images. However, the performance of RFCN and SSD/FSSD for large target detection was equal [5]. To distinguish automatically between potholes and destabilizations in the crowd sensing-based application sense caused by speed bumps or driver behavior, a deep learning technique was proposed to identify the various types of road surfaces. This method was essential for increasing the accuracy of pothole identification. In fact, the tests showed a higher rate of accuracy in real-world scenarios derived from daily travel [6]. The researchers proposed a deep-learning-based approach to monitoring road surface quality using accelerometer and GPS sensor readings.In this study, they used two approaches-SVM based approach Neural Network based approaches. By collecting copious amounts of data over the course of more than 36 hours on various types of roads, they show that the method can achieve high accuracy (98.5%) in a three-way classification of road surface quality [7]. Various deep learning models have been analyzed and implemented with the aim to automatically identify Pers Ubiquitous Computing on different kinds of road surfaces. They extracted 618 stability events, including 302 events linked to potholes and 218 events associated with speed bumps, taking into account the speed bumps and potholes that they had previously identified [8]. The use of low-cost camera footage to demonstrate a method of road detection that takes surface type variation into account with computer vision. Using ResNet34, they were able to train with a larger batch size and had a faster result. They reliably extracted helpful information on the condition of the road surface using only monocular video streams of standard resolution [9].

Test results confirmed the effectiveness of AMAC in acquiring road images. Two-line scan cameras mounted on a vehicle at an angle of about 30 degrees were used to capture images, and two laser illuminators were used to illuminate the road surface. They proposed a straightforward method for identifying cracks in the road's surface. The main point is that other dark zones appear erratically and discontinuously, whereas the crack is the darkest region and appears continuous in an image. The processing time of each image is 100 milliseconds. Crack pixels have been detected in digital images for the first time [10]. Up till now, a variety of innovative methods have been put forth for effectively identifying pavement cracks. Using a histogram of oriented gradient (HOG), Meng, Wang, Fujikawa, and Oyanagi have suggested an approach for fracture identification. With an unmanned helicopter, they captured images of the road surfaces and transmitted them wirelessly. The image has been binarized with thresholds of 55, 60, and 70, respectively. HOG was finally employed to find the fracture. However, they did permit a lot of noise in the picture [11]. For building an intelligent detection system of road surface cracks and to highlight the normally approached detection tools in the innovative detection technology of road surface cracks Yong Zhou et al. utilized with a ML and DL method on the custom dataset the authors collected with various sensors in various places and they got a higher accuracy in DL based model and more stable accuracy in ML-based model [12]. Dapeng Dong et al. utilized a method for eradicating extensive and costly road assessment, high time consumption and difficult monitoring condition of road surface. The authors collected the data on a neighborhood in Ireland through a smartphone application with several test-runs. These data were trained on successfully intensified proceedings utilizing the k-means ML algorithm with a test accuracy of 84% [13]. An innovative approach was developed by Rozi Bibi et al. for detecting broken and cracked road surfaces automatically by autonomous vehicles and informing the next vehicles with the road conditions built with VANET and Edge AI. The dataset used in the training part of the utilized model was collected from publicly available datasets. The dataset goes through two DNN named ResNet-18 and VGG-11 and scores an average test accuracy of 90% [14]. A novel DNN based model was proposed by Hongyi Zhang et al. for detecting road surface state following bad weather with autonomous vehicles in night time with a comparatively higher accuracy than the previous studies. The image dataset used in this study is collected from multiple public videos and for some of the DNN algorithms the data were collected manually. The proposed model scores an average of 94% accuracy with being built up with several DNN like ResNet, traditional CNN, VGG etc [15]. For balancing the disproportion of the datasets with the help of CycleGAN to raise the accuracy of road state detection architectures an innovative method was proposed by Wansik Choi et al. The dataset used in this study has a total of 20,000 street level images. The CycleGAN augmentation process helps the DNN based architecture to perform a decent accuracy of more than 85% on average [16]. Using our custom collected images augmented for the dataset, we are hoping to achieve a better accuracy while making sure the training time and resource needs are minimized to ensure better real time operation on weaker devices. Different deep learning models will be evaluated over our dataset and the best performing model will be selected as our proposed method of this work.

III. Methodology

The methodological segment of our conducted research is demonstrated hereby. This part consists of detailed information about the procedure of our dataset preparing, preprocessing and augmenting dataset, visualization of some samples of dataset along with the process of these. The classification problem which we attempt to solve through our proposed model is also talked over in this part of the paper. The models we are using for classification and the layers and parameters of the models are determined in consideration of the dataset we have prepared for the highest accuracy and least loss.

A. Dataset Collection

We have used a custom-made dataset in this classification problem of identifying road surface conditions. The dataset collection procedure started with taking photos of various roads from different parts of Dhaka city. The photos consist of multiple angles of the same roads along with some unique and one-angled photos only for variations in dataset. The majority of the photos are tried to be free from having any unnecessary obstacles so that the training can be done efficiently without worrying about the outlying obstructions. The dataset contains:

- 1614 images of Smooth, no damage or need of maintenance roads labeled as “Smooth Road”.
- 1614 images of roads that are partially damaged, severely damaged or immediately need repairs with the label of “Damaged Roads”.
- 80% of the total images are used for model training. Approximately 2583 images are labeled as the training portion.
- 10% of images (323 images) are separated from the training portion along with another 10% (323 images) for validation of the model.

B. Dataset Cleaning

As we are collecting dataset from outside running road scenarios, and we tend to keep only the images that do not contain any distractions rather than just the surface of the roads, we had to manually check all the images that were taken primarily. After selecting the target images, some of the images were seen to have blurry and exposure related issues that might affect the model negatively. These images were also dropped from the dataset and stored in local storage as well as cloud storage (Google Drive) for security purposes.

C. Dataset Preprocessing

The 1080*2400-pixel photos taken from the open scenario were of a high resolution and were not suitable for inclusion in our testing models. For convenience, we rescaled the photos using (1. /255), which changes the pixels’ range from (0,255) to (0,1), so that they contribute more equitably in the event of loss. The resolution of the preprocessed photos is maintained at 448*448 pixels. Additionally, a denoise method was conducted specifically to certain photos that contained minor amounts of noise but not enough to be noticeable.

D. Dataset Augmentation

After the dataset had undergone preprocessing, there weren’t many photos left. In order to increase the amount of

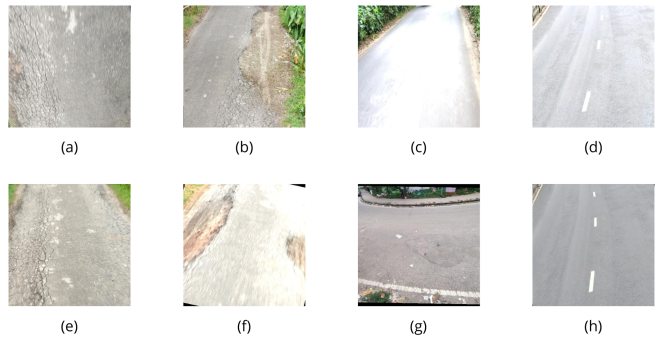

Fig. 2. Dataset Sample

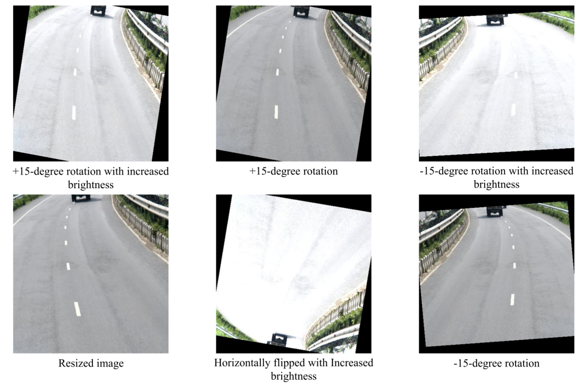

Fig. 3. Augmented Dataset

dataset and allow the model to operate even more precisely, we had to make some adjustments to the raw photos while taking into account that greatly increasing the number of images will lead to overfitting. The photos were rotated between -15 and +15 degrees, sheared within a range of 0.2, zoomed in and out inside a range of 0.2, and both vertically and horizontally flipped. Then, the fill type for the ImageDataGenerator method was fixed to constant so that the produced images do not contain any degraded areas rather than being black. The brightness range in which the images will indeed be varying at random was then selected from 0.5 to 1.5.

E. Proposed Network

When previous models are utilized to address a fresh challenge or issue, this is referred to as transfer learning in deep learning. Transfer learning is a methodology or strategy utilized when training models, not a specific kind of deep learning algorithm. In order to complete a new assignment, past training's knowledge is recycled. The specific work will be somehow connected to the one that was practiced; it might be something like classifying things in a particular file type. To adjust to the new, unobserved data, the old trained model often requires a significant amount of generalization. Here, three different deep learning algorithms have been implemented using this transfer learning approach that requires less resources while at the same time ensuring better accuracy from its pre-trained weights.

1) MobileNet-v2: A DNN which consists of 53 layers, is termed as MobileNet-v2. The ImageNet database contributes to a pretrained category of the channel that is trained on more than 1 million photos. The pre - trained network can classify photos into one-thousand different object categories. As we are attempting to use a transfer learning method, we found out that MobileNet-v2 with its pre-trained weights over the ImageNet dataset can help us achieve higher accuracy even more efficiently. MobileNet-v2 has been able to achieve 93.49% accuracy over our custom dataset where it has classified 145 smooth and 157 damaged roads accurately.

2) VGG19: An adaptation of the VGG model consisting of nineteen layers that has sixteen convolution layers, three fully connected layers, five MaxPool layers along with one SoftMax layer is commonly known as VGG19. By default, VGG19 works with a input shape of (224*224) that is not very convenient in terms of classifying our road surface detections. So, we changed the input shape to (448*448) and it resulted in a matrix shape of (448,448,3) in the input layer of the model. After training the model with a customized input layer, the predictions of damaged and smooth roads were 166 and 146 correct and 11 false predictions of smooth road surfaces that denote the accuracy of the model as 96.59%. Implementing and comparing three deep learning models: MobileNet-v2, VGG19 and VGG16, the observations of accuracy of these three demonstrates that VGG16 is performing with the highest accuracy among the three models and this can be proposed as our chosen network for our study of detecting road surface conditions

3) VGG16: One of the unrivaled computer vision models to date is CNN which is a variant known as VGG16. The analyzed versions of the networks and enhanced complexity along with the architecture of incredibly tiny (3*3) convolutional filters, demonstrates a significant advancement on state-of-the-art setups. The depth was increased to 16–19 weight layers, yielding around 138 trainable parameters. Here, we also edited the input layer and used (448*448) size of images with (448,448,3) matrix shape for better clarity. The tested accuracy was 97.52% on the test dataset portion.

F. Model Training

We implemented the dataset in all of the CNN-based architectures that we described above. However, VGG16 outperforms the rest of the CNN architectures. This reason led us to take the decision to propose our model using the VGG16 architecture. The next paragraphs will provide a complete explanation of the VGG16 architecture.

CNN can be known as a ConvNet, it can also be put in the bracket of ANN. A CNN is constituted of three types of layers: hidden, output, and input layers. VGG16 is one of the most well-performed CNNs in the space of DNN-based architectures. Developers of this CNN based model did an intensive analysis and utilized the depth with (3 × 3) convolution filter-based architecture. This utilization made

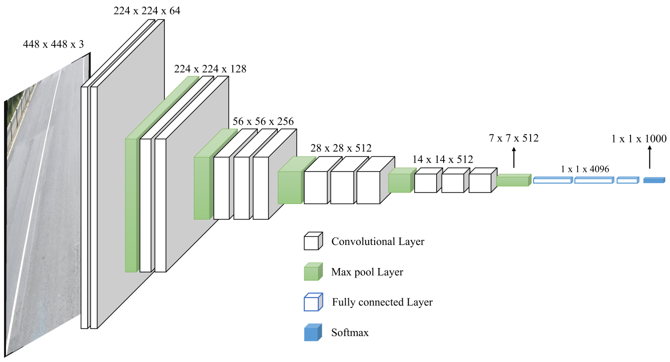

Fig. 4. Architecture of Custom Input Layered VGG16

TABLE I
COMPARISON OF PREVIOUS WORKS

Reference	Proposed Model	Augmentation	Dataset	Accuracy
Cheng et al., 2019[4]	A new activation function based on the ReLu	N/A	Oxford RobotCar and KITTI dataset	94.89%
Varona et al., 2020[8]	CNN	Applied	Applied	85%
Proposed Model	VGG16	Rotation, flipping, shearing, contrast	Custom	97.52%

a significant advancement over other state-of-the-art architectures. The depth was increased to 16–19 weight layers, yielding around 138 trainable parameters.

VGG16's 16th digit designates its 16 weighted layers. Three dense layers, five Max Pooling layers, and thirteen convolutional layers make up VGG16's total of 21 layers, although only 16 of those levels are weight layers, also known as learnable parameter layers. VGG16's input tensor size is 224 x 244 and it has three RGB channels. The most distinctive feature of VGG16 is that it prioritized convolution layers of a 3x3 filter with stride 1 rather than a large number of hyper-parameters and consistently utilized the same padding and max pooling layer of a 2x2 filter with stride 2. Throughout the whole design, the convolution and max pool layers are uniformly ordered. The Conv-1 Layer contains 64 filters, followed by Conv-2 with 128 filters, Conv-3 with 256 filters, Conv-4 with 512 filters, and Conv-5 with 512 filters. A stack of convolutional layers is followed by three Fully-Connected (FC) layers, the third of which performs 1000-way ILSVRC classification and has 1000 channels.The first two FC layers have 4096 channels each (one for each class). The soft-max layer is the last one.

G. Model Comparison

Deep learning techniques have been used in various works on road surface condition identification problems. The accuracy of some of the studies by other writers is comparable to our suggested model. The table that is included below provides a comparison between our work and the work of others.

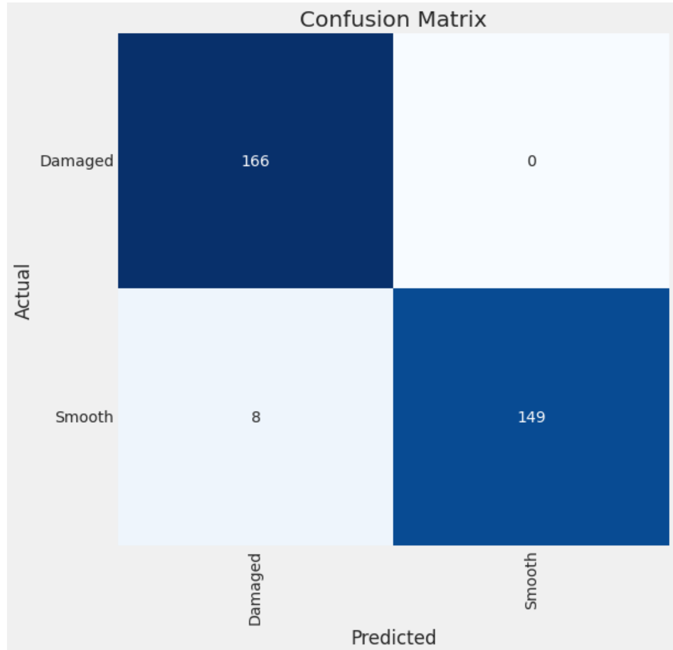

Fig. 5. Confusion Matrix of VGG16

IV. EVALUATING RESULTS

To get the best accuracy on our unique dataset, we have implemented three different deep learning models. VGG16, VGG19, and MobileNet-v2 have all been trained separately on our unique dataset using the transfer learning technique, decreasing the amount of time required while attempting training the model from scratch. Here, the transfer learning approach allows us to train over our unique dataset while maintaining the pre-trained weights of each model.

A. Generating Confusion Matrix

After a successful training session of VGG16, we may create a confusion matrix based on our model's predictions, which will provide a summary of our model's overall performance. The true-positives, true-negatives, false-positives, and false-negatives values in the confusion matrix are often defined as four separate values. We may calculate the precision and accuracy of the model using equations (1) and (2) using these four components from a confusion matrix table. The implementation of VGG16 with our dataset resulted in 166 and 149 correct detections of damaged and smooth roads chronologically. However, the model also predicted 6 of the test images as smooth roads but actually it was labeled as damaged roads. The confusion matrix is shown in figure 6.

B. Generating Classification ROC

Initially, using Keras Callback function, we ran 6 epochs of VGG16 where verbose was set to 2 and validation steps and shuffling was set to none. After 6 epochs of training,

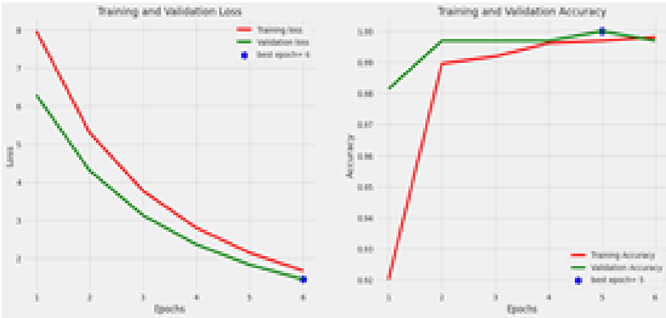

Fig. 6. Training Validation Curve

TABLE II
RESULT EVALUATION

DNN Model		Recall	F-1 Score	Precision	Accuracy
MobileNet-v2	C-1	1.00	0.94	0.88	93.00%
	C-2	0.87	0.93	1.00	
VGG19	C-1	1.00	0.97	0.94	96.59%
	C-2	0.93	0.96	1.00	
VGG16	C-1	1.00	0.98	0.95	97.52%
	C-2	0.95	0.97	1.00	

training and validation curves were observed in figure 7. The best epoch was recorded as epoch 5 with almost perfect training and validation accuracy but the loss did not seem very satisfying.

We can quickly establish a theory of which model is functioning with the highest capacity to detect photos from situations by looking at the comparison table between the models. Below is a table containing the results of each model along with their corresponding evaluation scores.

V. Conclusion

Reducing maintenance cost of repairing and re-building roads can be effective to the general public of a country by the contribution made to less frequent brutal accidents due to uneven road surfaces. As the population density increases over time, it gets more and more inadequate to the manpower handling the situations of the road infrastructures. Automating the monitoring task can be beneficial in terms of noting the parts of the road that need urgent repairing. Deep neural networks are proving their capability in detection of classifications problems these days. Combining these two, we proposed a model that can effectively identify road surfaces based on its training and storing the collected information in a local server. Our custom input layered model of VGG16 can achieve 97.52% accuracy on our custom dataset containing 3228 images. Later on, these data can come in handy while doing the other steps of road cares.

The one and only concern while undergoing this study was to collect appropriate data from roads as the native roads are over-crowded almost all the time and filled with vehicles. However, this hindrance was avoided by taking necessary initiatives to collect images of the roads on public holidays or whenever the roads are free of vehicles. Thus, this indicates the most challenging thing for us to ensure data availability. Our custom dataset only consists of images of a clear sunny day, some images from a rainy day or a foggy day could also affect the detection slightly, indicating a limitation of our work. In future, improving the dataset can be done using a better professional grade drone of which the footage will be from an angle of straight top and can also be more accurate to increase the overall quality of the dataset. Clearing the road surfaces completely of dust before attempting to shoot photos or videos for dataset can also be beneficial as expected.

References

[1] Road safety still a distant dream. Available online: Financial Express(accessed on: 14th August, 2022).
[2] World Health Organization. 2018. Road Traffic Injuries. Available online: World Health Organization.
[3] Varona, Braian, Ariel Monteserin, and Alfredo Teyseyre. "A deep learning approach to automatic road surface monitoring and pothole detection." Personal and Ubiquitous Computing 24, no. 4 (2020): 519-534.
[4] Cheng, Lushan, Xu Zhang, and Jie Shen. "Road surface condition classification using deep learning." Journal of Visual Communication and Image Representation 64 (2019): 102638.
[5] Zhang, Feng, Xiaoyu Wu, and Chaonan Gu. "Detection of road surface identifiers based on deep learning." In 2019 International Conference on Artificial Intelligence and Advanced Manufacturing (AIAM), pp. 66-70. IEEE, 2019.
[6] Behera, Bhagyalaxmi, and Rishi Sikka. "Deep learning for observation of road surfaces and identification of path holes." Materials Today: Proceedings (2021).
[7] Tiwari, Saurabh, Ravi Bhandari, and Bhaskaran Raman. "Roadcare: a deep-learning based approach to quantifying road surface quality." In Proceedings of the 3rd ACM SIGCAS Conference on Computing and Sustainable Societies, pp. 231-242. 2020.
[8] Varona, Braian, Ariel Monteserin, and Alfredo Teyseyre. "A deep learning approach to automatic road surface monitoring and pothole detection." Personal and Ubiquitous Computing 24, no. 4 (2020): 519-534.
[9] Rateke, Thiago, and Aldo Von Wangenheim. "Road surface detection and differentiation considering surface damages." Autonomous Robots 45, no. 2 (2021): 299-312.
[10] Sy, N. T., Manuel Avila, Stéphane Begot, and Jean-Christophe Bardet. "Detection of defects in road surface by a vision system." In MELECON 2008-The 14th IEEE Mediterranean Electrotechnical Conference, pp. 847-851. IEEE, 2008.
[11] Meng, Lin, Zhongkui Wang, Yoshiyuki Fujikawa, and Shigeru Oyanagi. "Detecting cracks on a concrete surface using histogram of oriented gradients." In 2015 International Conference on Advanced Mechatronic Systems (ICAMechS), pp. 103-107. IEEE, 2015.
[12] Zhou, Yong, Xinming Guo, Fujin Hou, and Jianqing Wu. "Review of intelligent road defects detection technology." Sustainability 14, no. 10 (2022): 6306.
[13] Dong, Dapeng, and Zili Li. "Smartphone sensing of road surface condition and defect detection." Sensors 21, no. 16 (2021): 5433.
[14] Bibi, Rozi, Yousaf Saeed, Asim Zeb, Taher M. Ghazal, Taj Rahman, Raed A. Said, Sagheer Abbas, Munir Ahmad, and Muhammad Adnan Khan. "Edge AI-based automated detection and classification of road anomalies in VANET using deep learning." Computational intelligence and neuroscience 2021 (2021).
[15] Zhang, Hongyi, Rabia Sehab, Sheherazade Azouigui, and Moussa Boukhnifer. "Application and Comparison of Deep Learning Methods to Detect Night-Time Road Surface Conditions for Autonomous Vehicles." Electronics 11, no. 5 (2022): 786.
[16] Choi, Wansik, Jun Heo, and Changsun Ahn. "Development of Road Surface Detection Algorithm Using CycleGAN-Augmented Dataset." Sensors 21, no. 22 (2021): 7769.