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Kamel Mahdy
Public Works Department, Faculty of Engineering; Ain Shams University; Cairo; Egypt, kamel.essameldeen@eng.asu.edu.eg

Ahmed Zekry
Electrical and Computer Engineering Department, Queens University

Mohamed Moussa
Geomatics Engineering Department, University of Calgary, Alberta, Canada; Public works department, Faculty of Engineering, Ain Shams University; Micro engineering Tech Inc.

Ahmed Mohamed
Geomatics Engineering Department, University of Calgary, Alberta, Canada; Micro Engineering Tech Inc

Hassan Mahdy
Professor, Public Works Department, Faculty of Engineering, Ain Shams University

See next page for additional authors

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REVIEW

Deep Learning Techniques for Efficient Evaluation of Asphalt Pavement Condition

Kamel Mahdy [a,*], Ahmed Zekry [b], Mohamed Moussa [c,d], Ahmed Mohamed [c,d], Hassan Mahdy [a], Mohamed Elhabiby [a,d]

[a] Public Works Department, Faculty of Engineering, Ain Shams University, Cairo, Egypt
[b] Electrical and Computer Engineering Department, Queens University, Ontario, Canada
[c] Geomatics Engineering Department, University of Calgary, Alberta, Canada
[d] Micro Engineering Tech Inc., Cairo, Egypt

Abstract

For the last few decades, researchers have been devising a simple and cost-effective method to evaluate pavement distresses to give decision-makers adequate feedbacks about the pavement condition of a certain road. Fortunately, with the evolution and progression of computer vision tools and techniques, good results had been achieved regarding the detection, classification, and quantification of road distress. In this paper, a new efficient process of road distress analysis using deep learning models is introduced. This new process was tested on a collected road dataset to evaluate the efficiency and speed of this low-cost road maintenance system. Promising results were obtained from the proposed process based on the deep learning model used with an outstanding performance of ~400 fps and distress detection every ~5 cm for a vehicle moving at 40 km/h. Furthermore, the output of the developed process was used as an input for the Pavement Condition Index (PCI) calculation module to determine the pavement condition of the road on a single-day mission. The proposed system focuses on detecting some specific types of distresses: Alligator cracks, longitudinal cracks, transverse cracks, block cracks, lane longitudinal cracks, reflective cracks, and sealed cracks. Experimental results show that this process based on deep learning models achieved promising results of ~5% difference from the true PCI, currently calculated in a month, just in a single day using very low-cost methods.

Keywords: Deep learning, Neural architecture search network (NASNET), Pavement, Pavement condition index (PCI), Pavement distresses, Pavement maintenance management system (PMMS), Pavement management system (PMS,)

1. Introduction

In 2021, nearly 41% of the United States federal transportation and infrastructure expenditure was directed toward highway transportation; this was more than 60 billion USD with an annual increase of ~20% from the previous year (USA Facts, 2022). Road quality is an essential part of a country's infrastructure and growth: It denotes its economic level, as defined by the World Bank as a rating indicator (Queiroz and Gautam, 1992). Considering this solid data, it is clear that every cent spent on maintenance of the highway road network will lead to savings of billions of dollars in the future. The highway road network that serves cities worldwide is comprised mostly of asphalt paved roads. For example, the US road network is over 6.58 million kilometers in length, approximately 65% of this is paved roads ('How Preventive Asphalt Road Maintenance, 2022). Needless to say, Asphalt pavement serviceability has a great impact on economic growth since it is a crucial component of the country's infrastructure and observing its condition is vital, since the degradation of its condition may result in inferior service quality of the whole transportation network. Therefore, early detection of pavement distresses and performing maintenance are essential to ensure pavement quality during its

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* Corresponding author at: Public Works Department, Faculty of Engineering; Ain Shams University, 41-11 Group 119, El Rehab city, Cairo, 11841, Egypt.
E-mail address: kamel.essameldeen@eng.asu.edu.eg (K. Mahdy).

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lifecycle as these have a positive impact on driving safety, socio-economic development of the country, and an acceptable level of road serviceability. Maintaining a pavement to be in good condition is four to five times less expensive than regularly renovating one that is in poor condition (Road Traffic Technologies, 2022). Studies like (Road Traffic Technologies, 2022) have proven that a poorly maintained system could increase life cycle costs. Recently (Mohamed et al., 2022a) reviewed and spoke about the efforts made by earlier studies to create mechanisms for making decisions on the construction and maintenance and repair (M and R) of flexible pavements at the project level. The study provided and conferred the favored perspectives of management strategies, system goals, system limitations, evaluation procedures, indicators, and models, as well as risk evaluations. As a result, many perspectives on the decision-making systems were discovered, and various restrictions and difficulties with regard to coming up with ideal plans were realized. Moreover (Mohamed et al., 2022b; Hall et al., 1991), presented some viewpoint reviews for mitigating the economic and environmental consequences triggered during the road pavement life cycle and reviewed the key findings of the prior studies. It was discovered that the management structure, rehabilitation tactics, and case setting all had intricate relationships with and significant effects on the induced costs to the economy and environment.

The organized practice of maintenance and rehabilitation works to maximize the benefits for transportation users and minimizes expenses to the administration or agencies responsible for pavement management. Acknowledged as the Pavement Management System (PMS), such a system allows agencies to assign resources, capital, staff, etc., efficiently (Tavakoli et al., 1992). A PMS is a system that involves the coordination, scheduling, and completion of all actions carried out by a highway agency to deliver acceptable pavement conditions for road users (Abo-Hashema et al., 2006). It is a highly structured, rational system that attempts to achieve the best usage of the available funds to provide pavements in good condition for the public. This can be done by comparing investment alternatives, design, construction, maintenance, and evaluation activities, and using available approaches and strategies. One of the most prominent methods of adding efficiency to the current processes is to develop predictive models (Younos et al., 2020) for the purpose of PCI calculations and estimations.

In this research, a less expensive and less labor-intensive full process for road pavement maintenance is explored. The process proposed is less accurate in PCI estimation by a difference of 5% from the true PCI estimate of the visual inspection method, but it provides accurate results to the ordinal PCI rating of Failed to Excellent. Meaning that this 5% error does not change the PCI ordinal rating from Failed to Very Poor or from Poor to Fair. In addition, using a video from a smartphone camera saves a lot of time and effort with a complete process instead of the current single deep learning model solutions.

2. Literature review

The pavement maintenance management system (PMMS), a branch of the Pavement Management System (PMS) (see Fig. 1), is a structured method for evaluating the condition of a given pavement Abo-Hashema and colleagues (Abo-Hashema et al., 2006). A cost-effectiveness analysis of different maintenance options is also performed by the system. Considering the available budget, the system can prioritize maintenance activities that ensure the best results. Each road section is inspected, visually or automatically, rated, and recorded on a database. The collected data are analyzed using pavement management software to provide recommendations and predict future pavement conditions.

2.1. Related works

A case study was conducted with the integration of new PMMS software with GIS Almuhanna and colleagues (Almuhanna et al., 2018). Calculated PCI values for a chosen zone of a 56.8 km long road network in Karbala, Iraq, using PAVER ('TM 5) and ArcGIS software. The crucial PCI value was used to illustrate the need for road network maintenance and rehabilitation. PAVER 6.5.7 was integrated with GIS to visualize the outputs and display the priority

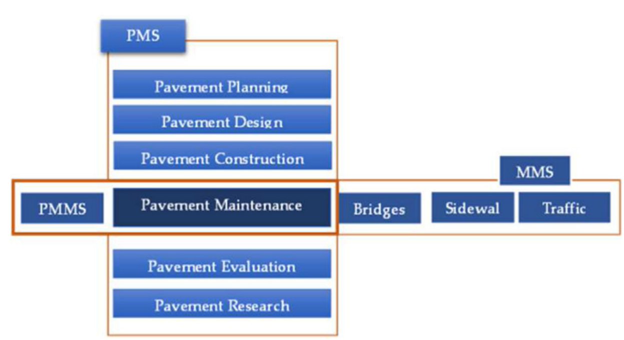

Fig. 1. Pavement maintenance management system (PMMS) and pavement management system (PMS) (Abo-Hashema et al., 2006).

for network maintenance and rehabilitation based on the crucial PCI value.

The aim of this was to give a wider overview of the related works regarding [mostly vision-based] automatic road analysis systems.

The main focus here is to introduce methods used by earlier systems and research Siriborvornratanakul (2018) used an Automatic Road Distress Visual Inspection System using an onboard camera to detect road stresses. This study focused on one specific type of pavement distress called potholes. Learning techniques of Support Vector Machine (SVM) and Local Binary Patterns (LBP) cascade classifier were used in this study comprising eight experiments on different images of potholes with different pixel size. This system setup was easy and low cost, though its obvious disadvantage was that it was not capable of detecting or recognizing road distresses with significant three dimensional visual characteristics.

Saar and Talvik (2010) proposed a detection and classification system using neural network focusing on Longitudinal, Transverse and Alligator cracks. The overall accuracy of this system was 89.3% when crack detection and classification were combined; 12% of the alligator crack images were classified as longitudinal or transverse cracking. This result could have been caused by thin cracks that the system was unable to detect Shen (2016) developed a model for crack detection based on video image processing by collecting images for different types of cracks and constructing a condition library for the road surface. With the aid of the skeleton extraction mathematical morphology method, the study successfully identified the crack category, and then created a pavement crack recognition software system using MATLAB software.

An AI based system was developed by Radopoulou and Brilakis (2017) that automatically detected several pavement distresses at the same time, such as longitudinal and transverse cracks, patches, and potholes using parking camera video data gathered from local streets in Cambridge, U.K., employing a semantic texton forests (STFs) algorithm as a supervised classifier. Accuracy reached by the system was over 82%, with a precision of more than 91% for longitudinal cracks, over 81% for transverse cracks, over 88% for patches, and more than 76% for potholes.

Novel methods of using machine learning and deep learning algorithms in calculating PCI are pioneered by the researchers in Majidifard and colleagues (Majidifard et al., 2020a). These researchers used the Yolo family of models, especially YoloV2 Redmon and Farhadi ('Redmon and Farhadi, 2017), to detect, classify, and localize distresses along the road. These authors also created a dataset Majidifard and colleagues (Majidifard et al., 2020b) from Google Images and labeled it to train and test the derived models. On using Google Images, some artifacts were revealed in the images, as shown in Radopoulou and Brilakis (2017), due to image stitching. Also demonstrated were the results from the Fast-RCNN model trained on the dataset. Almost all the models and algorithms discussed so far do not address the need for a real-time detection and classification of road distresses for the efficient and regular calculation of the road PCI.

In this paper, a novel method is introduced for the real-time detection and classification of different road distresses. This go further and perform PCI calculations on-the-fly. The new proposed method will usher the era of low-cost mobile road inspection units. A cost and time comparison between the conventional method of PCI calculation and the developed novel low-cost cloud-based deep-learning-based method (see Table 1).

3. Methodology

In this section, the proposed process and the methodology of testing in a real collected dataset are described. The process starts with a smartphone App to collect the positioned image frames for the road data acquisition process (see Fig. 2). Next, the App sends visual data to a deployed detection and classification model on a cloud service. Following that, a PCI calculation endpoint processes the output classification for PCI determination of the road.

The major advantage to the developed process is the low-cost of the hardware required for the data acquisition. In addition, the logistics need to include human and time resources at a significantly lower level. For the 40 km road section that was surveyed, data was collected for testing using a stop and go strategy in a 2–3 days' work load. In this process,

Table 1. Cost and time comparison between conventional and the proposed process.

Elements	Conventional method (Visual inspection) Cost/day (USD)	Our process Cost/day (USD)
Vehicle	25	25
Driver	20	20
Expert Engineer	25	–
Technical office Engineer	20	20
Cloud services	–	5
Time Taken	2 months	1 day
Cost/120 Km	5400	70
Cost/1 Km	45	0.58

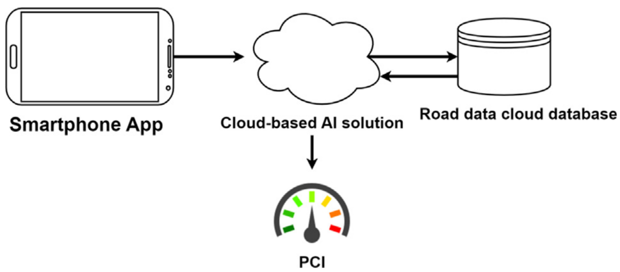

Fig. 2. High-level architecture of the proposed low-cost cloud-based road PCI calculation process.

1 h of driving time plus a fraction of that for the data processing is needed. This leads to a significant saving of time and resources.

3.1. Data acquisition app

The data acquisition App was developed to work on Android smartphones, collecting camera and location data. The collected data are then uploaded to cloud storage. In this case, Amazon Web Services (AWS) were used for all the cloud services needed, e.g., storage, APIs, deep learning model deployment, etc.

The smartphone was tested in two scenarios, attached with a holder to the wind shield, and attached directly to the vehicle bumper. Having the phone attached to the vehicle bumper enabled the capturing of more road portions and from an optimal angle for the images captured.

An advantage for placing the smartphone holder on the windshield is that it will be safer, particularly during rain or snowy weather. However, in this case, the main testing dataset was collected in Upper Egypt on Desert Road, so the smartphone being positioned on the bumper was not an issue, and the output images were clear for the model to detect.

3.2. Deep learning model

In this sub section the model used for training and testing of the road distress classification problem are described. The problem dictates that an image classification model is used. The problem is seen as a multi-class image classification, i.e., the model takes as input a single frame RGB image and outputs the probability of the existence of the distress class in the present two-dimensional image. Following this, the training procedure was explored. Training the model had different objectives than the nominal objective of accuracy enhancement. Using the Neural Architecture Search Network (NASNET) mobile model advantages, the model was trained to reach at least the same accuracy while maintaining the small size and fast inference properties of the backbone model. In the Results section of this paper, a comparison of the results of two different models are presented signifying the state-of-the-art performance of the deep learning model. In addition, the results are presented after the successful deployment of this model to an AWS Sage Maker endpoint as part of the PCI calculation process.

3.3. Model architecture

The model used, which is based on the NASNET-Mobile model Zoph and colleagues (Zoph et al., 2018), is a backbone model. The model has many advantages regarding the efficiency, speed, and model size optimization. The NASNET family of deep learning models were designed by the Google Brain team Majidifard and colleagues (Majidifard et al., 2020b). These models have a unique feature. Their model architecture resulted from rigorous training and testing for the best possible model design architecture and hyperparameter tuning. This means that the model layers are highly optimized to give the best possible results for a given problem. This type of classification model is fairly recent and, by using the output of a deep learning approach to come up with the architecture for another deep learning problem, it is very innovative. The usability of the NASNET family of models will be tested in the problem at hand, as these have proven to be efficient for solving such problems.

The NASNET-Mobile model consists of several building blocks (see Fig. 3). The number and order of these building blocks were estimated out of a learning-based approach. The exact model mentioned in Majidifard and colleagues (Majidifard et al., 2020b) is shown in Fig. 3. The building blocks used are called cells.

The NASNET-Mobile model utilizes two types of cells, namely, a normal cell, and a reduction cell. The algorithm behind the NAS, stands for Network Architecture Search, model optimization is to estimate

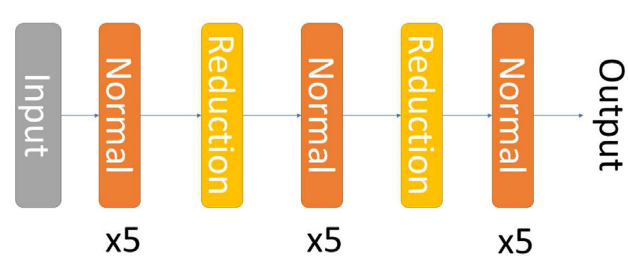

Fig. 3. NASNET model architecture as consecutive normal and reduction cells.

the number of consecutive normal and reduction cells to fit the performance requirements of the problem and dataset at hand. As opposed to the classical grid search approaches, NAS models search for the architecture properties of the deep neural network. In this research, the reduced version of the original model, NASNET-Mobile was used.

This version of the NASNET model comes with only 5 normal cells per normal layer. The normal cell layers are interleaved with reduction cells. The main difference between the reduction cell and the normal cell is that the reduction cell starts with a bigger stride. The larger stride is important to scale down the size of the feature maps along the network chain of cells. So, map size reduction is the responsibility of the reduction cells, hence the name. This kind of architecture comprising of two standard cell structures give more flexibility to change and explores different architecture performances.

A model head with the suitable number of distress classes was added. The model is estimating the probability of the following road distresses: Reflective Cracks, Block cracks, Alligator cracks, Sealed transverse cracks, Sealed longitudinal cracks, and Lane longitudinal cracks. The cross-entropy loss in equation (3.1) was used for computing the loss during the training of the model.

$$L = -\sum_{i=0}^{5} t_i \, log(p_i) \tag{3.1}$$

Where t_i is the true label and p_i is the output probability that this distress exists in the current input frame.

3.4. Training procedure

For the deep learning model training, a dataset made available by the researchers in Radopoulou and Brilakis (2017) was used. The dataset comprised of 7237 labeled images collected from Google Street map images and manually labeled by experts for the different road distress types. The model used was trained for 50 epochs on a batch size of 32 images. The images needed to be resized as a preprocessing step before the input layer for the model could be finalized. A head of different classification classes was added to the model to define the output classes of the road distress features. The dataset was split into 70% training and 30% testing sets. The mini-batch was shuffled every epoch during training. The model was trained on an RTX 2070 GPU and tested on the same GPU before being deployed to the AWS Sage Maker endpoint.

3.5. Cloud-based deployment

The cloud solution starts with an upload of the captured images (see Fig. 4). The cloud services used were AWS API Gateway, which received requests with the uploaded image stream. The tested images were then uploaded to an S3 bucket storage. Afterwards, an AWS Lambda function was triggered whenever a new test image was present in the S3 bucket. This function is a script that pre-processes the image, sends it to the deployed deep learning model, and then interprets the output results. In the end, the result was added to a record base for PCI calculation and stored in another S3 bucket. The image with the location and distress type is then used to determine whether there is a distress in that location. With these results a database of georeferenced road distresses is built. The process does not classify the severity, so an average severity to be medium is assumed. In future work a more precise model to determine the severity of the road distress is targeted.

3.6. Process testing dataset

The dataset collected for the testing and validation of the process was derived from a 50 km road section on the Upper Egypt Desert Road between Beni Suef and El-Minia (see Fig. 5). The vehicle had the data collection App installed on the smartphone attached to the bumper. One-way drive was collected in one of the two-lane road.

The output dataset had a low angle (see Fig. 6), where the smartphone collecting data was attached to the vehicle bumper. The vehicle was driving at a 120 km/h speed. The dataset was in the form of 20 k low resolution frames of highway road section.

4. Results

First, the model's results shown in Table 2 will be discussed on the road distress classification problem

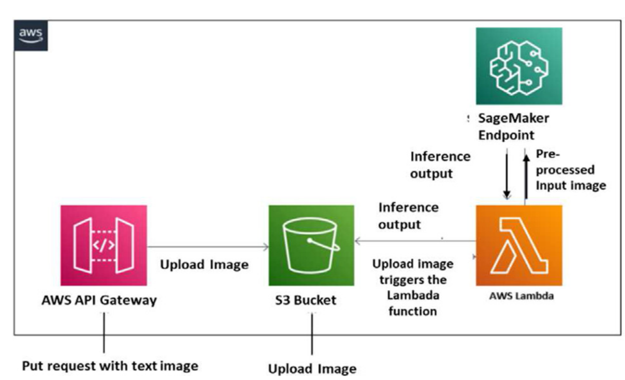

Fig. 4. System architecture for the cloud-based AI road distress detection and classification service.

Fig. 5. Upper Egypt Desert Road dataset collected for process testing and verification.

with the objective of achieving the maximum possible performance, in terms of speed and model size, using the minimum acceptable accuracy. The models were tested to be mobile-ready so that they could be used in real-time road inspection units. Then, the overall performance of the PCI calculation will be presented on the cloud-based process.

4.1. Evaluation metrics

The precision, recall and F1-score error metrics are the suitable metrics for the application. The precision represents a measure of how many correct detections to the total number of detections from the model. The recall is a measure of how many correct detections to the total number of distress cases in the dataset. An F1-score is an average of both metrics.

The same evaluation metrics were used as the ones used in Radopoulou and Brilakis (2017). The weighted F1-score is the most accurate error metric to use for this application. Therefore, the results could be easily compared with Radopoulou and Brilakis (2017) state-of-the-art results. Also compared were hardware performance and model size to show how superior this model is compared with the models these previous researchers resorted to. Further, this shows how compatible this new model is for real-time applications.

Fig. 6. A sample frame from the Upper Egypt Desert Road dataset.

4.2. Experimental results

As depicted in Table 3, the 5% and 10% are PCI values. The 10% PCI was calculated using manual visual inspection, while the 5% PCI was calculated using the deep-learning-based process. The proposed model slightly outperformed the Faster.

R−CNN model in the average weighted F1-score. As for the model size, a 90% reduction was achieved, compared with the most accurate Yolo-v2 model size. It also achieved 87.5% reduction in size compared with Fast-RCNN, the smaller of the two models. In terms of speed, this new model achieved 4x frames per second metric, which makes it 4x times faster than Yolo-v2, the fastest of the two models in Radopoulou and Brilakis (2017).

Although, the proposed model did not exceed the Yolo-v2 model in terms of overall accuracy using the weighted F1-score metric, it did achieve an overall recall score of 100%. This means that the developed model gave zero false negatives through the whole testing set of the dataset. This recall score was crucial for the calculation of the PCI score of the road, because false negatives in the model output will lower the overall score for the road and may result in the decommissioning of the road for maintenance purposes, while not reflecting the real PCI. The developed model's 100% recall score will save additional costs due to the unnecessary maintenance and road closures.

In addition, the proposed model's F1-score achieved higher results than the Faster-RCNN model. This deemed the use of the Faster-RCNN model useless compared with this new model that performed better in terms of accuracy, speed, and size.

Furthermore, the proposed model outperformed the Yolo-v2 model in classification of the sealed transverse cracks and lane longitudinal cracks, which are two of the most important and widely common road distresses along highways. It also, came very close to the performance of the Yolo-v2 model in classifying the reflective cracks.

4.3. Process results

When testing the new process on the Upper Egypt Desert Road 50 km dataset, two methods of PCI calculation were compared. The first was the traditional stop-and-go visual inspection. The low-cost

Table 2. Training results compared with the models in (Radopoulou and Brilakis, 2017) trained on the same road distress dataset.

	Yolo v2			Faster R–CNN			Proposed model		
Distress type	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Reflective Crack	0.93	0.76	0.84	0.73	0.72	0.72	0.7	1.0	0.82
Block crack	0.93	0.79	0.85	0.82	0.59	0.68	0.44	1.0	0.61
Alligator crack	0.91	0.74	0.82	0.81	0.43	0.57	0.15	1.0	0.27
Sealed transverse crack	0.93	0.83	0.87	0.83	0.68	0.75	1.0	1.0	1.0
Sealed longitudinal crack	0.93	0.79	0.85	0.81	0.54	0.65	0.26	1.0	0.42
Lane longitudinal crack	0.94	0.57	0.71	0.75	0.3	0.42	0.63	1.0	0.78
Average	0.93	0.74	0.82	0.79	0.54	0.63	0.53	1.0	0.65
FPS	93			30			410		
Model size	202.7 MB			159.74 MB			20.6 MB		

Table 3. PCI calculation tests between conventional methods and our proposed process.

	Conventional method (Visual inspection)	Proposed process
Calculated PCI	10%	5%
Time Taken	25 days	~1 day

cloud-based process was then used to demonstrate the advantages of the new method. The results, shown in Table 3, reveal that the proposed low-cost cloud-based deep learning process can get a PCI calculation accurate to a 5% difference of the true PCI in 1 day of operation, and at a much lower cost as that shown in Table 1, compared with the conventional visual inspection methods that consumes time and human resources.

5. Future work

As noted thus far, the proposed technique outperformed the comparison the other approaches in terms of size and speed, while giving an above average performance, sometimes even outperforming other deep learning models for some distress types. These results will be enhanced by labeling the resultant new road distress dataset and use that for the training, testing, and evaluation of the proposed model in comparison to other models solving the same road distress problems.

In addition, the proposed process doesn't currently provide a way to determine the severity of the distress. In future work, a pixel-based semantic segmentation model is to be used with image depth estimation to provide an accurate severity estimate for each distress in the image.

The proposed model will also be tested with that of the original NASNET-Large model to evaluate the performance of the mobile version to a non-real-time one. It is expected that the proposed model will outperform the other two models and become the new state-of-the-art system in the road distress classification problems.

5.1. Conclusion

In this paper, a new low-cost cloud-based deep learning approach was proposed for near-real-time PCI calculation. Within the developed process, a real-time mobile-ready classification deep learning model was designed for the road distress inspection application. The proposed process produced a PCI accurate to 5% difference from the true PCI produced by the manual visual inspection approach. The used deep learning model showed 87.5–90% reduction of model size and ~400% increase in model inference speed compared with the current road distress deep learning models state-of-the-art. It also showed that the proposed mobile model outperformed the state-of-the-art system in most common road distress features. These results have the potential to lead to a breakthrough in the economics of road inspection methods.

Authors contribution

The authors contributed to the following: 1. Mahdy Kamel. a. Pavement Data gathering. b. Resources. c. Data analysis and interpretation. d. Methodology. e. Creation of the Deep Learning detection Model. f. Drafting the article. Ahmed Zekry. a. Methodology. b. Software. Mohamed Moussa. a. Methodology. b. Critical revision of the article. Ahmed Mohamed. a. Software. Hassan Mahdy. a. Conception or design of the work. b. Supervision. Mohamed Elhabiby. a. Project administration. b. Funding acquisition. c. Resources. d. Critical revision of the article.

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Conflicts of interest

The authors declare that there are no potential conflicts of interest with respect to the research, authorship or publication of his article.

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