Road Rutting Detection using Deep Learning on Images

Poonam Kumari Saha  
Center for Spatial Information Science  
The University of Tokyo  
Tokyo, Japan  
poonamkumarisaha@g.ecc.u-tokyo.ac.jp

Deeksha Arya  
Center for Spatial Information Science  
The University of Tokyo  
Tokyo, Japan  
deeksha@iis.u-tokyo.ac.jp

Hiroya Maeda  
Founder, President, and CEO  
Urban-X Technologies, Inc.  
Tokyo, Japan  
hiroya_maeda@urbanx-tech.com

Ashutos Kumar  
Center for Spatial Information Science  
The University of Tokyo  
Tokyo, Japan  
ashutos@csis.u-tokyo.ac.jp

Abstract—Road rutting is a severe road distress that can cause premature failure of the road incurring early and costly maintenance costs. Research on road damage detection using image processing techniques and deep learning are being actively conducted in the past few years. However, these researches are mostly focused on the detection of cracks, potholes, and their variants. Very few research has been done on the detection of road rutting. This paper proposes a novel road rutting dataset comprising 949 images and provides both object-level and pixel-level annotations. Object detection models and semantic segmentation models were deployed to detect road rutting on the proposed dataset, and quantitative and qualitative analysis of model predictions were done to evaluate model performance and identify challenges faced in the detection of road rutting using the proposed method. Object detection model YOLOX-s achieves mAP@IoU=0.5 of 61.6% and semantic segmentation model PSPNet (Resnet-50) achieves IoU of 54.69 and accuracy of 72.67, thus providing a benchmark accuracy for similar work in future. The proposed road rutting dataset and the results of our research study will help accelerate the research on the detection of road rutting using deep learning.

Index Terms—Road Rutting, Deep Learning, Object Detection, Image Segmentation, Road Damage Detection, Big Data Applications

I. INTRODUCTION

Road rutting is considered a severe pavement damage [1] and is crucial in the planning of road maintenance. It affects pavement structural integrity and can cause premature failure of road surfaces. Its presence increases the possibility of hydroplaning, where water or ice accumulates in the ruts leading to the loss of grip between the pavement and the vehicle tires, as well as steering problems [2]. This negatively impacts the safety of the driving public by causing undesirable vehicle vibration and instability. Therefore, there is a need to monitor road conditions and repair road rutting regularly or before it becomes severe.

Traditional methods perform inspections manually or using specially designed vehicles equipped with sensors and laser technology, etc. These may give accurate results but are very expensive to implement and maintain. High cost acts as a bottleneck in effective road maintenance especially when the budget is decreasing [3]. Further, failed pavements require costly maintenance and repair which in turn cause restrictions in traffic flow. Therefore, there is a need for an easy and efficient method to detect instances of road rutting in order to assist in prompt maintenance and early rehabilitation of damaged roads.

Recent research has shown the potential of using image processing techniques and deep learning in the detection of road damages ([4], [5], [6], [7]). Most of the past research ([7], [8], [9]) including Global Road Damage Detection Challenge (GRDDC) organized as a part of the 2020 IEEE International Conference on Big Data [10] in this direction focused on the detection of cracks, potholes, and their variants. However, road rutting detection using deep learning still remains an open research problem. To the best of our knowledge, there is no pre-existing road rutting dataset, and presently even if it exists, the instances of road rutting are grouped with other categories such as bumps, blurring, potholes, etc. Further, its instances are remarkably less than those of other damage types. This not only affects its detection accuracy [11] but also makes it unsuitable for detecting it individually as a separate category.

This paper addresses these needs and makes the following contributions in this area:

1) Proposes a road rutting dataset containing 949 images collected from heterogeneous sources.
2) Provides data annotation in both object-level bounding box and pixel-level formats.
3) Proposes object detection as well as semantic segmentation models capable of detecting road rutting and presents a benchmark for its detection accuracy.
4) Comprehensively analyses the challenges faced in the detection of road rutting using deep learning.
As compared to the traditional methods, the proposed method requires less resources. It is easy to standardize and reproduce. The addition of more training data and improvement in deep learning techniques in future will only make this method better and stronger.

The rest of the paper is organized as follows. In section II, related works are discussed. Details of the proposed dataset and methodology are explained in section III. Results are provided in section IV. Discussion on the results is provided in section V. Finally, section VI concludes the paper.

II. RELATED WORKS

This section describes existing methods and research works related to the detection of road rutting, ranging from traditional methods to modern machine learning-based methods. Further, image processing and deep learning-based methods are focused and thereafter, the availability of road rutting datasets, object detection models, and image semantic segmentation models are discussed.

A. Traditional Methods of Road Rutting Detection

Many traditional methods are based on the measurement of road rut depth. This is done either manually or using equipment such as laser scanning technology ([3], [12]), profilometers equipped with infrared sensors, rut bar collection system, ultrasonic technology [13], etc. Authors in [14] have deployed a photographic data collection system using a camera and a strobe and used Pavement Distress Analysis System (PA-DIAS) for doing measurements. Although these quantitative inspections may be accurate, conducting such comprehensive inspections are expensive, especially for small municipalities that lack the required financial resources. Further, these methods are very specific to the detection of road rutting and cannot be generalized to detect other road damages. Furthermore, the use of specialized vehicles with high-precision sensors to collect road condition data requires dedicated infrastructure and manpower which makes it expensive [15]. The high cost can discourage municipal road maintenance bodies to perform frequent monitoring trips given the limited availability of allocated funds and manpower.

B. Predictive Models using Machine Learning Techniques

Recently proposed methods for road rutting detection involve the collection of road rutting data such as depth, width, the radius of curvature of ruts; temperature, pavement age, and other factors related to the permanent deformation of the section, etc. The data so obtained is then used to compute some of the pavement performance indices or establish relationships amongst different factors using machine learning to develop predictive models. Authors in [16] and [17] have developed pavement rutting models by applying machine learning on road data. Since different methods and different combinations of factors are considered at different places and these analyses being done are very specific to the location, it is challenging to generalize these practices across the country or globe. These limitations reiterate the need for an automated damage detection technology that requires less resources and is easy to implement, standardize, and reproduce.

C. Road Damage Detection using Image Processing and Deep Learning

Recent research has shown impressive results in road damage detection using image processing and deep learning. Extensive research has been done to detect road cracks and potholes such as in [9], [18], [19], [20], etc. Authors in [21] have used fully convolutional network (FCN) and faster region-based convolutional neural networks (Faster R-CNN) for road damage detection in Naples (Italy), but their dataset contains only one instance of road rutting out of a total of 8736 road damage instances. Authors in [6] have used single shot multi-box detector (SSD) with Inception V2 and MobileNet for road damage detection in their proposed dataset, RDD2018, for Japan, but their dataset groups rutting with other road damages such as blur, separation, and pothole. Their model resulted in low recall of this category which was attributed to less number of training data. The RDD2018 dataset was extended to include images from multiple countries in RDD2020 [22] and RDD2022 [23]. However, the extended datasets do not include road rutting.

D. Available Road Rutting Dataset

The road damage datasets made available by the works of [6], [18], [22], [24], [25], etc. mainly contain instances of cracks, potholes, and their variants. In contrast, the road damage dataset proposed in [26] contains 263 images of road rutting. However, these images are captured perpendicularly above road surfaces and are not wide-view images obtained from vehicle-mounted cameras or smartphones.

E. Object Detection Models

An object detection model finds the number of objects in an image and estimates bounding box coordinates for each object along with its category. These are broadly classified into two categories: two-stage detectors and one-stage detectors. A two-stage detector detects objects by first making a region proposal based convolutional neural networks (Faster R-CNN) for road damage detection using image processing and deep learning. Extensive research has been done to detect road cracks and potholes such as in [9], [18], [19], [20], etc. Authors in [21] have used fully convolutional network (FCN) and faster region-based convolutional neural networks (Faster R-CNN) for road damage detection in Naples (Italy), but their dataset contains only one instance of road rutting out of a total of 8736 road damage instances. Authors in [6] have used single shot multi-box detector (SSD) with Inception V2 and MobileNet for road damage detection in their proposed dataset, RDD2018, for Japan, but their dataset groups rutting with other road damages such as blur, separation, and pothole. Their model resulted in low recall of this category which was attributed to less number of training data. The RDD2018 dataset was extended to include images from multiple countries in RDD2020 [22] and RDD2022 [23]. However, the extended datasets do not include road rutting.

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F. Image Semantic Segmentation Models

It is a form of pixel-level prediction as it assigns a class label to every pixel in an image. It classifies a certain class of image and separates it from the rest of the image classes by overlaying it with a segmentation mask. It outputs the bounding box around and segmentation mask on the object when an input image is fed to the network. These models have been used in our study to analyze if it affects the detection accuracy of road rutting by using only a segmentation mask in order to avoid the additional information that gets enclosed while using a bounding box in the object detection model. The image semantic segmentation models used in the current study are PSPNet (Resnet-50) [37] and DeepLabv3+ (Resnet-101) [38].

III. METHODOLOGY

The methodology consists of four steps: data collection and dataset preparation, annotation of data, performing object detection and image semantic segmentation to determine the feasibility of detection of road rutting and quantitative and qualitative evaluation of results and analysis of possible challenges faced in detection.

A. Data Collection

In our research, a novel road rutting dataset has been developed from heterogeneous sources. Three sources are considered, details of which are presented in Table I. The images are mostly wide-view road images extracted from videos captured by onboard vehicle cameras or smartphones. The videos have been collected in March 2021 and between March and April 2022 under varying weather and lighting conditions. A dataset of 949 images was finally created after careful selection from over 100,000 images. The selection criteria involve discarding of following types of images:

- Blurred images
- Images with dark shadows
- Images that don’t contain significant portions of the road
- Images that don’t contain road rutting
- Images containing shadows of overhead electric wires

(The reason for this is explained in section V).

Samples of discarded images are illustrated in Fig. 1.

B. Data Annotation

Each image has been manually annotated in a semi-automatic way to provide annotations in both object-level and pixel-level formats. In the object-level annotation, bounding boxes have been made using an annotation tool labelImg [41]. The annotations are saved in YOLO labelling format which is a .txt file. At first, 308 images were annotated manually which were used to train a YOLOv4 model. This model was then used incrementally to annotate images from each subsequent source. The annotations were checked manually using the labelImg tool, and this process was repeated. In the pixel-level annotation, semantic segmentation masks have been created using a data labeling tool called Label Studio [42]. “Semantic Segmentation with Masks” was used. This uses a brush to draw the region on the image. The masks were exported in PNG format. This was used in training the semantic segmentation models in our study. In addition to masks using brush, masks using polygons have also been considered which saves the annotations in COCO format which is a .json file. Object-level bounding box and pixel-level mask annotations of an image are illustrated in Fig. 2.

C. Data Statistics

The proposed road rutting dataset has 949 images containing 904 instances of rutting. The entire dataset is randomly split in the ratio of 85:15. A set of 806 images was used for training and that of 143 images was used for testing. During the initial training, it was observed that the model made false predictions in images containing zebra crossing, sidewalks, having corrugated surfaces near the road, and shadows of trees or colorful patchwork on road surfaces. Therefore, negative samples without bounded boxes were included in the dataset to help the model learn better. This is in accordance with instructions on improving detection accuracy as per [33]. Consequently, the images which don’t contain rutting have been included in the dataset, some of which are shown in Fig. 3.

Our proposed dataset is publicly available and can be downloaded from https://github.com/sekilab/RoadRutting [43].
TABLE I: Details of Road Rutting Dataset

| Sources                                                                 | Locations                        | Image Size  | Image Type | No. of Images |
|------------------------------------------------------------------------|----------------------------------|-------------|------------|---------------|
| Images extracted from videos captured by on-board vehicle cameras or smartphones | Susono City [39]                 | 1280 × 720  | PNG        | 34            |
| Mapillary Street-level Sequences Dataset [40]                         | Maebashi and Hida City           | 1920 × 1080 | PNG        | 240           |
| Web scraping and captured by smartphone                               | Tokyo                            | 640 × 360   | JPG        | 575           |
| Web scraping and captured by smartphone                               | Meguro and others                | variable    | JPG        | 100           |

Fig. 3: Images of negative samples: (a) contains corrugated surfaces in walls nearby road surface, (b) contains zebra crossing and sidewalks, (c) contains shadows of tree, and (d) contain colorful patches on road surfaces

D. Road Rutting Detection using Object Detection Model

The study involves training and evaluation of object detection models using YOLOv4, YOLOv5, YOLOv6, and YOLOX. Their pre-trained weights trained on the COCO dataset were utilized to train the requisite road rutting detection models using transfer learning. The models have been trained on the image size of 416 × 416 and evaluated at confidence threshold 0.25 and IoU threshold 0.5 as suggested by Pascal VOC Challenge [44] on the test dataset. The model weights with the best mAP on the test dataset were chosen for all future evaluation purposes.

Further, image augmentation techniques using albenations [45] were explored with the objective to improve the detection accuracy of the YOLOv4 model. Horizontal flip, random brightness contrast, Gaussian noise, RGB shift, sharpen, etc. were used in accordance with techniques mentioned in [22]. However, the vertical flip was not used as images with the vertically flipped roads will not appear in the real-world dataset while taking videos or images using dashboard cameras on vehicles. For the augmented dataset, the mean Average Precision at the Intersection over Union 0.5 (mAP@IoU=0.5) for YOLOv4 was found to be 32.2% which is slightly lesser than the mAP@IoU=0.5 of 33.7% obtained by YOLOv4 on the dataset without image augmentation. For YOLOv5, Test Time Augmentation (TTA) was performed. The mAP@IoU=0.5 improved from 34.4% for the YOLOv5 model without TTA to only 34.7% for the YOLOv5 model with TTA.

Since the results using image data augmentation didn’t provide significant improvements, it was not explored further.

E. Road Rutting Detection using Image Semantic Segmentation Model

Another aspect that arises is if the detection accuracy of road rutting can be improved by using segmentation masks instead of bounding boxes. The reason for considering this aspect stems from our preliminary visual analysis of the results of object detection-based models. The use of a bounding box while annotating road rutting in an image can include additional information about the surrounding along with the rutting instance. The use of multiple smaller bounding boxes instead of a single larger bounding box can help address this challenge to some extent, but in doing so, some smaller portion of the rutting instance can itself get excluded. However, the use of segmentation masks can ensure that no additional information about surroundings is included in the annotation. This study involves training and evaluation of image semantic segmentation models using PSPNet (Resnet-50) and DeepLabV3+ (Resnet-101). For details, readers may refer to OpenMMLab’s MMSegmentation, which is an open-source semantic segmentation toolbox [46] based on PyTorch.

IV. RESULTS

In our experiment, training of the deep learning models was performed on an AWS instance type named g4dn.xlarge running on the Ubuntu 18.04 operating system. It has one NVIDIA-T4 GPU with 16 GiB GPU memory. Sample model predictions are illustrated in Fig. 4.

A. Performance of Different Object Detection Models

This study considers mAP@IoU=0.5 as the quantitative measure to compare the performance of different object detection models. This measure has the advantage that it provides a single value for each object detection model to compare its performance with other object detection models. The higher the value of mAP, the better is the performance of the model. Table II presents mAP obtained by different object detection models used in the study. YOLOX achieved the maximum mAP value amongst the trained models, and amongst the variants of YOLOX, YOLOX-s achieved the highest mAP value. One possible reason for YOLOX-s giving higher mAP than those by YOLOX-m or YOLOX-l is that since YOLOX-s is a lightweight model, its chances to overfit with less training data might be low.
TABLE II: Performance of Object Detection Models used in the study

| Model name         | mAP@IoU=0.5 (%) |
|--------------------|-----------------|
| YOLOv4             | 33.7            |
| YOLOv5-l           | 34.4            |
| YOLOv6-s (finetune)| 26.9            |
| YOLOv6-s           | 20.3            |
| YOLOX-s            | 61.6            |
| YOLOX-m            | 59.7            |
| YOLOX-l            | 55.0            |

B. Performance of Different Image Semantic Segmentation Models

This study considers Intersection over Union (IoU) and Pixel Accuracy (Acc) as quantitative measures to compare the performance of one semantic segmentation model with that of another. IoU is considered to be better than pixel accuracy as the latter is not suitable when one class overpowers the other. In the present case, background and rutting become two classes and in most images, background accounts for a larger area than rutting does. Therefore, the semantic segmentation model with greater IoU will be considered better. Table III lists the result of semantic segmentation models used in this study. Both the semantic segmentation models used in the study achieve IoU above 52 and accuracy above 72.

C. Visual Analysis of Predicted labels and Masks

Visual or qualitative analysis of the ground truth and predicted labels and masks was performed with the following two objectives:

1) To evaluate and compare the performance of the object detection model and semantic segmentation model as these are two different approaches of deep learning to identify and localize the object in the image, and these don’t have common evaluation metrics to compare their performances.

2) To comprehensively analyze the predictions and identify the challenges in performing road rutting detection.

The following observations were made during the visual or qualitative analysis:

- It was found on visual checking of the predicted labels or masks that all the studied models were able to correctly predict the road rutting instances on most images.
- The inclusion of negative samples improved the model performance. All the models correctly identified images containing zebra-crossing and sidewalks as non-rutting.
- All the object detection models except YOLOv5 incorrectly predicted rutting on some of the images with red colorful patches on road surfaces. YOLOv6 also made false predictions on some images containing shadows of trees on the road and nearby road surfaces having differences in heights. In most cases, all the models incorrectly predicted dark shadows of overhead electric wires which are longitudinal to the road as rutting. The samples of wrong predictions by object detection models are shown in Fig. 5.
- Unlike object detection models, semantic segmentation models made correct predictions in the above cases except for shadows of overhead electric wires.
- It was noted that the bounding boxes predicted by YOLOX were larger in size and had higher confidence scores as compared to those of other object detection models used in the study.

V. DISCUSSION

The initial success achieved by these training models in the detection of road rutting using image dataset strongly suggests that the deep learning-based detection models can be used in the detection of road rutting, and it will work even more efficiently when trained on a significantly larger training dataset. More training data will improve the accuracy of prediction [47].

Further, there cannot be a single correct bounding box or image mask for road rutting in the image. The labels or masks predicted by both object detection and semantic segmentation models are acceptable when a comprehensive survey for monitoring road conditions is required. However, since these models compare the predicted labels or image masks with the information in the ground truth for evaluation...
applications as road rutting is a severe road damage type besides cracks, and potholes and its identification as a separate category is important to enable road managers to take effective remedial actions. This will be helpful in giving a boost to the collection of more road rutting dataset as the majority of the present research focus more on the collection of a dataset containing images of cracks and potholes.

VI. CONCLUSION

In our research, we developed a novel road rutting dataset containing 949 images from heterogeneous sources. We used the state-of-the-art object detection models, namely YOLOv4, YOLOv5, YOLOv6, and YOLOX, and semantic segmentation models, namely PSPNet (Resnet-50) and DeepLabv3+ (Resnet-101) to study the feasibility of detection of road rutting using deep learning. We performed a quantitative and qualitative analysis of the models and their prediction to evaluate their performance, make comparisons, and to identify challenges faced in performing this task using the proposed method. Object detection model YOLOX-s achieves mAP@IoU=0.5 of 61.6% and semantic segmentation model PSPNet (Resnet-50) achieves IoU of 54.69 and accuracy of 72.67. Besides quantitative results, visual or qualitative analysis of model predictions helped find out that the deep learning models used in the study provided stable predictions in validating images.

In continuation of the research work, we want to further increase the road rutting dataset and combine it with the already existing road damage dataset containing cracks, potholes, etc. to develop a comprehensive model for road damage detection.

REFERENCES

[1] Japan International Cooperation Agency (JICA). Road pavement hand-book for jica grant aid projects, 2020.
[2] Michael Mamlouk, Mounica Vinayakamurthy, B Shane Underwood, and Kamil E Kalouch. Effects of the international roughness index and rut depth on crash rates. Transportation research record, 2672(40):418–429, 2018.
[3] Kazuyuki Kubo. Pavement maintenance in japan, 2017.
[4] H Bello-Salau, AM Aibina, EN Onwuka, JJ Dukiya, and AJ Onumanyi. Image processing techniques for automated road defect detection: A survey. In 2014 11th International Conference on Electronics, Computer and Computation (ICECCO), pages 1–4. IEEE, 2014.
[5] Madhura Katageri, Manisha Mandal, Mansi Gandhi, Navin Koregaonkar, Prof Sengupta, et al. Automated management of pothole related disasters using image processing and geotagging. arXiv preprint arXiv:1610.08808, 2016.
[6] Hiroya Maeda, Yoshilide Sekimoto, Toshikazu Seto, Takehiro Kashiyama, and Hiroshi Omata. Road damage detection and classification using deep neural networks with smartphone images. Computer-Aided Civil and Infrastructure Engineering, 33(12):1127–1141, 2018.
[7] S Jana, S Thangam, Anem Kishore, Venkata Sai Kumar, and Saddapalli Vandana. Transfer learning based deep convolutional neural network model for pavement crack detection from images. International Journal of Nonlinear Analysis and Applications, 13(1):1209–1223, 2022.
[8] Braham Bemmhafe and Jihane Alami Chentoufi. Automated pavement distress detection, classification and measurement: A review. International Journal of Advanced Computer Science and Applications, 12(8), 2021.
[9] Ce Zhang, Ehsan Nateghinia, Luis F Miranda-Moreno, and Lijun Sun. Pavement distress detection using convolutional neural network (cnn): A case study in montreal, canada. International Journal of Transportation Science and Technology, 11(2):298–309, 2022.
Ephrem Taddesse. Intelligent pavement rutting prediction models: the case of norwegian main road network. In Proceedings of the international conferences on the bearing capacity of roads, railways and airfields, pages 1051–1060, 2013.

Angela J Haddad, Ghassan R Chehab, and George A Saad. The use of deep neural networks for developing generic pavement rutting predictive models. International Journal of Pavement Engineering, pages 1–17, 2021.

Peggy Subirats, Jean Dumoulin, Vincent Legeay, and Dominique Barba. Automation of pavement surface crack detection using the continuous wavelet transform. In 2006 International Conference on Image Processing, pages 3037–3040. IEEE, 2006.

K Vigneshwar and B Hema Kumar. Detection and counting of pothole using image processing techniques. In 2016 IEEE International Conference on Computational Intelligence and Computing Research (ICICIC), pages 1–4. IEEE, 2016.

Yuki Bhatia, Rachna Rai, Varun Gupta, Naveen Aggarwal, Aparna Akula, et al. Convolutional neural networks based potholes detection using thermal imaging. Journal of King Saud University-Computer and Information Sciences, 2019.

Gioele Ciaparrone, Angela Serra, Vito Covito, Paolo Finelli, Carlo Alberto Scarpato, and Roberto Tagliaferri. A deep learning approach for automatic crack detection from pavement images. Construction and Building Materials, 283:122668, 2021.

Maha Rajab, Mohammad H Alawi, and Mohammed A Saif. Application of image processing to measure road distresses. WSEAS Transactions on Information Science & Applications, 5(1):1–7, 2008.

Amy Louise Simpson. Measurement of rutting in asphalt pavements. PhD thesis, The University of Texas, Austin, 2001.

Zhenyu Du, Jie Yuan, Feipeng Xiao, and Chamod Hettiarachchi. Application of image technology on pavement distress detection: A review. Measurement, 184:109900, 2021.

Deeksha Arya, Hiroya Maeda, Sanjay Kumar Ghosh, Durga Toshniwal, Hiroshi Omata, Takehiro Kashiyama, and Yoshihide Sekimoto. Global road damage detection: State-of-the-art solutions. In 2020 IEEE International Conference on Big Data (Big Data), pages 5533–5539, 2020.

Sarah Arezoumand, Ahmadreza Mahmoudzadeh, Amir Golroo, and Barat Mojaradi. Automatic pavement rutting measurement by fusing a high speed-shot camera and a linear laser. Construction and Building Materials, 283:122668, 2021.