Detection of asphalt roads degradation using Deep Learning applied to Unmanned Aerial Vehicle imagery

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Abstract

Asphalt roads deteriorate over time due to wear and tear, weather conditions and the effect of traffic loads. These degradations cause enormous damage to road users and economic losses to countries. In Senegal, the inspection of roads for maintenance purposes is done by field surveys and measurements, which is tedious, slow and expensive. This paper proposes a solution for automatic detection of the degraded state of paved roads using Deep Learning applied to drone imagery. The methodology includes three phases: collection of pavement images by drone, processing (annotation, training and detection) of the images by YOLOv8 and localization of degraded areas on GeoTiff results of reconstructed pavements. The model was trained and tested on a dataset with a wide range of pavement images and the results show a precision rate of 86.7%, a recall rate of 78.8% and an F1 score of 82.5%.

Keywords: Deep Learning · degradation of asphalted roads · detection · Unmanned Aerial Vehicle images · YOLOv8

1 Introduction

Road infrastructure is a factor in the economic and social development of countries. Good quality bituminous pavements contribute to the safety and comfort of road users. Although designed to withstand bad weather and the effects of traffic, pavements are subject to deterioration due to wear and tear, poor operation or poor quality of work. In Senegal, several sections of paved roads in urban and inter-urban areas are experiencing various forms of deterioration, some of which are advanced. This has a serious impact on road traffic and the country's economy. Thus road maintenance remains an unavoidable task and the Autonomous Agency for Road Works (AARW) schedules periodic road maintenance works. In order to optimise these works, a preliminary evaluation of the state of the roads is carried out to survey the geometry of the road network and to have precise information on their level of deterioration. However, this assessment requires technical teams to travel to the field for visual inspection, photography of the points observed and geometric surveys. This is tedious, slow and costly, especially when large sections of road are to be inspected. To overcome these problems, technological road monitoring tools are being developed to characterise the condition of pavements. Among these tools, solutions based on aerial photography are emerging as an alternative for large-scale road mapping. And with the progress made by artificial intelligence, Maching Learning algorithms allow the automatic detection of pavement deterioration on the images collected. Several

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scientific works have focused on road inspection with machine learning models. This article proposes a Deep Learning approach based on drone imagery for the detection of asphalt road deterioration. The rest of the paper is organised as follows: Section 2 gives an overview of related work on the subject. Section 3 describes the working methodology and the materials used. We present the results in Section 4 and discussions in Section 5.

2 Related works

In order to improve the performance of road condition inspection, several research efforts aimed at automating defect detection have been undertaken. Wang et al. [1] and Schnebele et al. [2] conducted a comprehensive review of different computer vision techniques applied to roads and pavements to detect potholes and distresses using unmanned aerial vehicles. Their study found that the most common methods for detecting cracks were laser and digital cameras. While for potholes, SVM and CNN based approaches are used. Guan et al. [3] proposed an automated pavement distress detection framework incorporating stereo vision and Deep Learning to efficiently achieve crack and pothole segmentation at the pixel level. Their overall precision and recall rates are 0.9632 and 0.9552 respectively. Koch et al. [4] presented a method for automated pothole detection in asphalt pavement images. Their methodology, implemented on a MATLAB prototype, was trained and tested on 120 pavement images. The results gave an overall accuracy of 82% with a recall rate of 86%. Lin et al. [5] proposed a VMS-based algorithm to identify a related region and discriminate whether it is a pothole based on a segmented pavement defect image. Their experimental results show that the algorithm can achieve a high recognition rate. Azhar et al. [6] addressed pothole detection and location using computer vision. They computed the features of the histograms of oriented gradients (HGO) for the input images and trained the features using the Na¨ıve Bayes classifier. To locate the pothole in the detected images, they used a normalized graph cut segmentation scheme. Their accuracy rate is 90Other authors [7-10] have proposed solutions for assessing ruts and potholes on the road surface using a UAV. The drone was used to collect data from the road and algorithms were used to process and detect anomalies in the images. Several other research studies [11-14] have focused on the use of Deep Learning algorithms to detect cracks, ruts and potholes in roads. However, this work does not take into account all the forms of deterioration commonly encountered. Also, the location of degraded areas is not taken into account in most previous research.

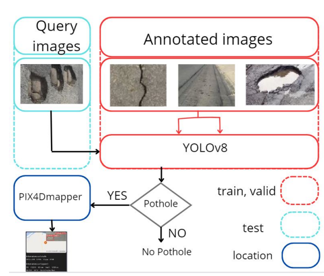
3 Materials and method

3.1 Forms of pavement damage

Pavements are subject to climatic conditions and various stresses whose direct effects cause the deterioration of bituminous surfacing. The most common types of deterioration encountered in Senegal are structural deterioration and surface deterioration. The former appear within the structure of the pavement or its support, while the latter originate in the surface layer of the pavement and affect its surface qualities [15]. This study deals with the detection of surface distresses classified into three groups (fig1.a): cracking, as evidenced by cracks and crazing, pavement deformation, as evidenced by ruts, and pothole tearing. These forms of deterioration are the most frequent on the road network in Senegal [15].

(a) crack (b) crazing (c) rut (d) pothole

(a) Distress typ



(b) Method algorithm [6]

Figure 1: Distress typ and method algorithm

3.2 Method

The method proposed in this work is an approach to detect, count and locate pavement degradations. It includes the collection of images, the processing (annotation, training and detection) and the positioning of the damage (Fig1.b).

(a) An RTK UAV collects the images of the roadway with the geographical coordinates. The drone performs the collection mission in linear flight at an altitude of 10m and captures the images using an RGV camera with an overlap rate of 80%.

(b) The annotation of the images is done using the Roboflow tool. The types of road degradation (crack, rut and pothole) have the same label ”Pothole” on the annotated images. The model is implemented on YOLOv8 which is the latest version of the YOLO series, released on 10 January 2023 by Ultralytics. It is an excellent choice because of its speed, accuracy and ease of use [16] compared to previous versions.

(c) To localize the degradations detected on the inspected roads, the PiX4Dmapper tool is used. The images from the detection are exported from the YOLO results folder and then loaded into the Pix4Dmapper software by mission in order to be aligned. For more precision in the alignment, the images are captured with an overlap rate of 80%. Then the points containing the location informations in 3 dimensions (X, Y and Z) thanks to stereoscopy, are extracted to reconstruct and export the final result in GeoTiff format.

3.3 Materials and tools

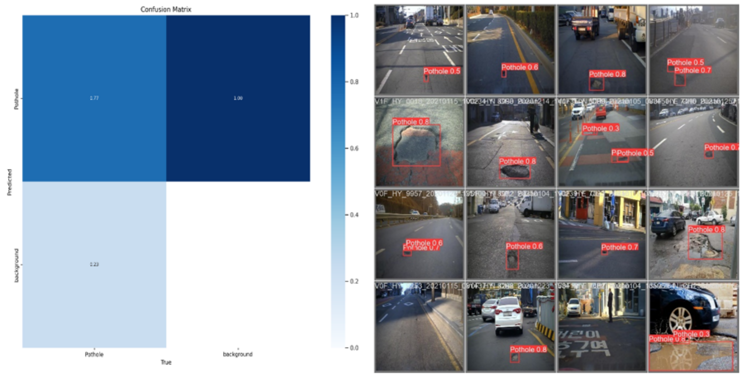
For the collection of geo-referenced images of the road, a DJI Phantom 4 RTK UAV was used with the characteristics presented in the table 1. This drone is best suited for photogrammetry work requiring centimeter accuracy. The most accurate metadata are recorded in each photograph captured by its 20MP CMOS camera. The experimentation is performed under YOLOv8 on an HP EliteBook Intel(R) Core(TM) I7-7600U, CPU @ 2.8GHz 2.9GHz with 16GB of RAM. The algorithm was programmed in Python3 under the Google Colab Notebook: backend Google Compute Engine Python3.9.16; RAM 12.68GB; Disk 78.19GB. The alignment of the images for the localization of the degradations on the roads is done through the Pix4Dmapper 4.7.5 software.

3.4 Dataset

The model was trained and tested on an image database consisting of a set of 9240 pavement images distributed as follows: 6091 model training images, 2094 images for validation and 1055 test images. The images are annotated with Roboflow and a part of the dataset (train, valid) has been provided in open access by the Roboflow platform [19]. The images collected by the drone are used to test the detection of the trained model. The collection concerned some road sections showing signs of degradation in Senegal. The images were captured by the Dji phantom 4 RTK drone programmed for automatic mapping missions. A total of five collection missions were carried out in linear flight at an altitude of 10m and the images were captured using an RGV camera with a recovery rate of 80%. Fly 1: 151 images; fly 2: 297 images; fly 3: 321 images; fly 4: 130 images and fly 5: 156 images.

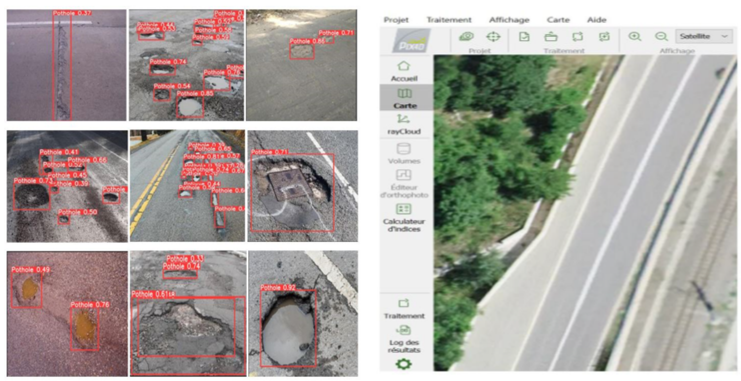
4 Results

The pre-trained weight yolov8x was used for training, validation and testing of the model due to its performance. The number of epochs was set to 100 and the image size to 1280 for training. The images collected by the drone for the model detection test have a resolution of 4864x3648 corresponding to the 4:3 format. The model detected each drone image at a speed of 1.3 ms. The metrics used to evaluate the performance of our model were computed by Roboflow 100 and are: mean accuracy (mAP), precision, recall and F1 score. The confusion matrix of the model (fig1.a) shows the following detection rates: mAP 84.4%, precision 86.7%, recall 78.8% and the F1 score 82.5%. These rates show a good performance of the model which some detection results are illustrated on (fig3.a). The four forms of degradation are detected with a confidence threshold varying between 0.25 and 0.98. The true negative (TN) rate is high for the cracks and slightly for the fissures. The images resulting from the detection were aligned on the Pix4Dmapper tool in order to have an exported result in GeoTiff format (fig3.b). This format can be used to locate each degraded area.



a) Confusion matrix b) Prediction validation

Figure 2: Train and validation results



a) Detection results b) GeoTiff image

Figure 3: Detection and location results

5 Discussions

This work consisted in building a model to detect pavement degradation states using drone and Deep Learning. The detection test involved data from different portions of roads affected by degradation in Senegal. The results are satisfactory in spite of some cases of false negatives observed on roads with an advanced level of deterioration. Indeed, when the number of cracks, crazing or potholes is high in an area, some of the defects escape the model. Thus our model presents inferences with false negatives in these rather degraded zones. This is also related to the accuracy in annotating the training images because the test images have a larger size than the training images of the model. The coordinates of the location of the degradation area are given with enough precision after the alignment of the images in GeoTiff format. Overall, the results are quite accurate and can be used by technical services for road maintenance work.

6 Conclusion

In this paper, we presented the detection and localization of degradations of asphalt roads using Deep Learning based on drone imagery. The characteristics of the degraded pavements have a semantic relevance and the forms of degradations concerned are cracks, ruts and potholes. The method is based on the YOLOv8 model which is the latest version of the YOLO series. Using the metrics, we evaluated the performance of the model and the results are satisfactory with an accuracy rate of 86.7%. Nevertheless, a slight false negative rate is observed for cracks, crazing and potholes in areas with high density of degradation. The results of the reconstruction of the different segments concerned by the inspection give enough precision in the location of the degraded zones.

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