Real time road defect monitoring from UAV visual data sources

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ABSTRACT

The use of UAVs and artificial intelligence has emerged as a promising approach for monitoring road defects. This paper highlights the importance of these technologies in improving road inspection, maintenance, and safety. Traditional methods for inspecting roads are often time-consuming, expensive, and can put human inspectors in dangerous situations. However, drones equipped with high-resolution cameras and sensors can capture pavement image data quickly and safely. Deep learning algorithms can then analyze this data to identify and localize areas in need of repair. By leveraging these technologies, engineers and road construction experts can more efficiently monitor and maintain roads, reducing the costs associated with repairs and maintenance, while in parallel improving safety. To this end, this work emphasizes the potential of UAVs in conjunction with deep learning techniques to provide a more comprehensive view of road conditions, allowing for targeted repairs and more effective maintenance strategies, such as prefabrication and robotic interventions. Experimental results using objective evaluation criteria, such as precision, recall, F1-score, and IoU are promising, which entails that this study advocates for the adoption of these technologies to enhance the monitoring and maintenance of road infrastructures.

CCS CONCEPTS

• **Computing methodologies**; • **Artificial intelligence**; • **Computer vision**; • **Computer vision problems**; • **Object detection**; • **Computer vision tasks**; • **Scene understanding**;

KEYWORDS

Object detection, UAV image processing, Road infrastructure monitoring, Computer vision

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1 INTRODUCTION

Inspections of civil engineering structures, such as road infrastructures, are carried out by technicians utilizing rope and harness access equipment, in conjunction with construction machineries such as lifts and cranes. These traditional inspection techniques not only pose safety risks, that may lead to worker injuries and accidents, but are also costly and time-consuming. Furthermore, they require heavy machinery that results in hindrances in road and waterway traffic. It is also noted that the identification of the damaged areas is performed using visual methods, potentially leaving damage unnoticed in the inaccessible areas of the structures. Therefore, it is mandatory to adopt innovative inspection methods, through which efficient defect identification is promoted, while in parallel the workers' safety is ensured [1].

On this basis, unmanned aerial vehicles (UAVs) offer several advantages in processes that involve remote sensing data acquisition. More specifically, by exploiting drone technology we are able to remotely, and therefore safely, collect data from otherwise virtually or physically unreachable areas. Also, we can effectively gather timely and on-demand images [2], by avoiding short-term traffic arrangements, that require time-consuming permits and result in traffic jams, shutdowns, accidents, and CO_2 emissions. Hence, it is underlined that UAVs are emerging as a suitable and cost-effective method for gathering high-quality image data, that encompass key spatial, textural, and chromatic information of the under-inspection structure [3].

The use of drones will favor the monitoring of road infrastructures that are difficult to access, and in the case of road maintenance, they will allow having a current model of defects to plan automated actions for the next day's maintenance tasks, avoiding visual inspection of the personnel (driving vehicles and walking on the road) and therefore, possible accidents [4]. Drone technology will make it possible to reduce the overall cost of these expensive interventions. Consequently, the use of aerial drones can provide the bigger picture of the area under maintenance or/and upgrading intervention procedure [5].

In parallel, the effective inspection of road defects is a critical task for engineers as it helps to ensure the safety and longevity of road infrastructures. Traditional methods of inspecting roads can be time-consuming, expensive, and often lack accuracy, making it difficult

to identify defects before they cause major problems. However, the advent of deep learning algorithms has provided a new and more effective approach to road defect inspection. By analyzing large amounts of data, deep networks can identify, classify and localize even the smallest cracks or potholes, allowing for targeted repairs and more effective maintenance strategies [6 - 8]. To this end, in this paper, we evaluate the effectiveness of a YOLO object detector that utilizes UAV imagery, to create an image-based automated solution for effective road defect detection and classification [9 - 11].
The remainder of the paper is organized as follows. In the rest of section 1, we provide an overview of related work on road defect detection as well as our contribution to the field. In section 2, we describe the proposed method in detail, as well as its architecture. In section 3, we present the utilized dataset, training procedure, and experimental results as well as analyze the performance of our proposed method. Finally, we conclude the paper in section 4 and discuss potential future work in the field of road defect detection and classification.

1.1 Previous Work

The literature presents various noteworthy attempts at studies for road infrastructure monitoring with deep learning techniques. Object detection methods can apply to different aspects of the above-mentioned issue. The work of [12] presents a single shot detection and classification of road users based on the real-time object detection system YOLO. This method is applied to the pre-processed radar range-Doppler-angle power spectrum.

Obstacle recognition on road images is another aspect of object detection [13]. The work of [14] implemented an obstacle detection and avoidance driverless car using Convolutional Neural Networks (CNNs). In the study of [15] a deep learning system, using Faster Region-based convolutional neural network was employed for the detection and classification of on-road obstacles such as vehicles, pedestrians, and animals. Tsung-Ming Hsu et al. presented a deep learning model to mimic driving behaviors by learning the dynamic information of the vehicle along with image information in order to improve the performance of a self-driving vehicle. For the implementation of the model, they placed traffic cones on the road to collect the scene of avoiding obstacles [16].

The work of [17] investigates road surface monitoring equipped with GPS and inertial sensors: an accelerometer and a gyroscope. It implements wavelet decomposition analysis for signal processing of inertial sensor signals and Support Vector Machine (SVM) for anomaly detection and classification. The paper of [18] proposes a system to autonomously and comprehensively monitor road infrastructure conditions. They suggest methods that could incorporate an automatic collection of ground truth data for supervised machine learning.

In parallel, the work of [19] focuses on a segment-based spatial stratified heterogeneity method, which is utilized to explore the comprehensive impacts of vehicles, climate, properties of road, and socioeconomic conditions on pavement infrastructure performance. Segment-based optimal discretization is applied to discretizing segment-based pavement data, and a segment-based geographical detector is utilized to assess the spatial impacts of variables and their interactions. The findings indicate that the quantified comprehensive impacts of variables are practical for wise decision-making for road design, construction and maintenance. The paper of [20] focuses on the deployment of different Machine Learning (ML) algorithms, such as Support Vector Machine, Random Forest, Naïve Bayes, Artificial Neural networks or convolutional neural networks in order to make research on ML-based pavement evaluation. Lastly, the work of [21] moves in the same direction and compares five different algorithms to inspect the contents of images, Region-based Fully Convolutional Network (R-FCN), Mask Region-based Convolutional Neural Networks (Mask R-CNN, Single Shot Multi-Box Detector (SSD), RetinaNet and YOLOv4, for vehicle safety systems purpose.

1.2 Our Contribution

Inspired by the aforementioned studies, in this paper, we present the development of an object detection deep learning framework based on the YOLOv5 architecture for the automated inspection of road infrastructures by utilizing UAV images. The use of deep object detection techniques in road infrastructure monitoring is crucial for the timely detection and repair of defects. Traditional methods of road inspection are often limited in their ability to identify defects in real-time, resulting in increased costs and potential safety hazards. Thereby, such technologies can quickly and accurately identify and localize defects such as cracks, potholes, and other damage, allowing for targeted repairs and more effective maintenance strategies [22]. As such, the implementation of AI frameworks in road infrastructure monitoring has the potential to significantly improve safety and reduce costs associated with road repairs and maintenance.

Moreover, UAVs have become an essential tool for monitoring road infrastructure defects due to their ability to capture high-resolution images and data from difficult-to-reach areas. Therefore, their use can significantly improve the efficiency and accuracy of road inspections, reducing costs associated with repairs and maintenance while enhancing safety. Consequently, the proposed methodology addresses existing limitations in maintenance and upgrading by incorporating UAV and robot-assistive road infrastructure processes that (i) increase automation in the inspection and maintenance process, (ii) minimize traffic delays during inspection and maintenance, and (iii) improve workers' safety and avoidance of weather hazards.

2 OBJECT DETECTION MODEL

As already mentioned, our work is based on top of the YOLOv5 object detection model. YOLO is a fast real-time multi-object detection algorithm, which was first outlined in 2015 [23] and since its first inception, many modifications have been proposed to improve and speed up the detection process. YOLO is an acronym for "You only look once" and is a target detection algorithm based on a regression algorithm that uses Neural Networks to provide real-time object detection. Its usefulness comes due to the fact that it completes the prediction of the classification and location information of the objects according to the calculation of the loss function, so it transforms the target detection problem into a regression problem [24]. This algorithm uses the most advanced detection technologies

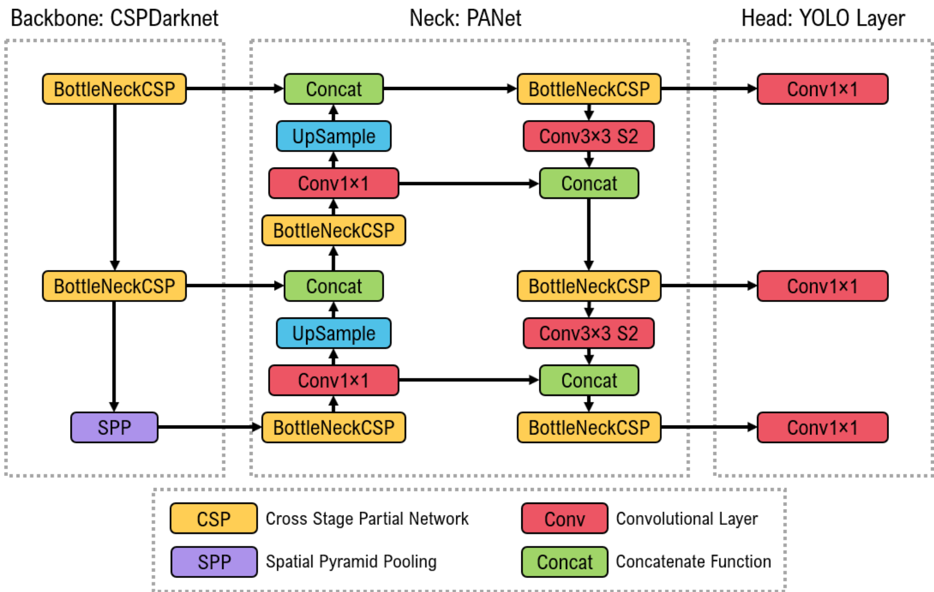

Figure 1: The architecture of the model YOLOv5, which consists of three parts: (i) Backbone: CSPDarknet, (ii) Neck: PANet, and (iii) Head: YOLO Layer. The data are initially input to CSPDarknet for feature extraction and subsequently fed to PANet for feature fusion. Lastly, the YOLO Layer outputs the object detection results (i.e., class, score, location, size).

available at the time and optimizes the implementation for best practices [25].

In this implementation, we utilize YOLOv5, which holds state-of-the-art performance among the various YOLO algorithms. It is based on the PyTorch framework and its functionality comes from the fact that it is a suitable lightweight detector that can balance detection accuracy and model complexity under the constraints of processing platforms with limited memory and computation resources [26]. As can be seen in Figure 1 the architecture of the model YOLOv5 consists of three parts: (i) Backbone: CSPDarknet, (ii) Neck: PANet, and (iii) Head: YOLO Layer. The data are initially input to CSPDarknet for feature extraction and subsequently fed to PANet for feature fusion. Lastly, the YOLO Layer outputs the object detection results (i.e., class, score, location, size).

3 EXPERIMENTAL EVALUATION

3.1 Dataset Description

In order to train and evaluate the YOLOv5 model the dataset that is presented in the work of [4] was exploited. The data (see Figure 2) was created in order to represent the situation of the Spanish roads and automate the detection of two main types of road damage, i.e., potholes and cracks. The dataset utilized for the evaluation of the results of the specific scientific article has been made publicly available to the scientific community for testing new networks and verifying the results.

In particular, initially, it contained 568 labeled road images, with a resolution of 3840×2160 pixels, from RGB sensors mounted on a UAV. After the pre-processing process, the total number of labeled images in the dataset was 1,362 images. More specifically, the following pre-processing process was applied to each RGB image:

- Auto-orientation of pixel data (with EXIF-orientation stripping)
- Resize to 1200×900 [Fill (with center crop)]

Furthermore, in order to generalize the detection capabilities of the trained model, the following augmentation process was applied in order to create three versions of each source UAV image:

- 50% probability of horizontal flip
- 50% probability of vertical flip
- Random rotation of between -15 and +15 degrees
- Salt and pepper noise was applied to 5 percent of the pixels

Thereby, after the preprocessing procedure among the 1,362 UAV images, 70% were used for training (1,191 images), 20% for validation (114 images), and 10% for testing (57 images) the detection capabilities of the trained deep model.

3.2 Experimental setup - Model training

The YOLO object detector was trained and evaluated using an NVIDIA Tesla K80 GPU with 12 GB of memory, provided by Google Colab. We trained the network, using batches of size 32, for 200 epochs, and set the input image resolution to 448×448 pixels. This work is based on the YOLOv5 small model in order to reduce the computational cost of the detection task. Towards this direction, the network takes up less than 15 MB of storage and thus can be easily embedded in smartphone applications and various low-memory digital devices or systems [27], including drones and microcontrollers.

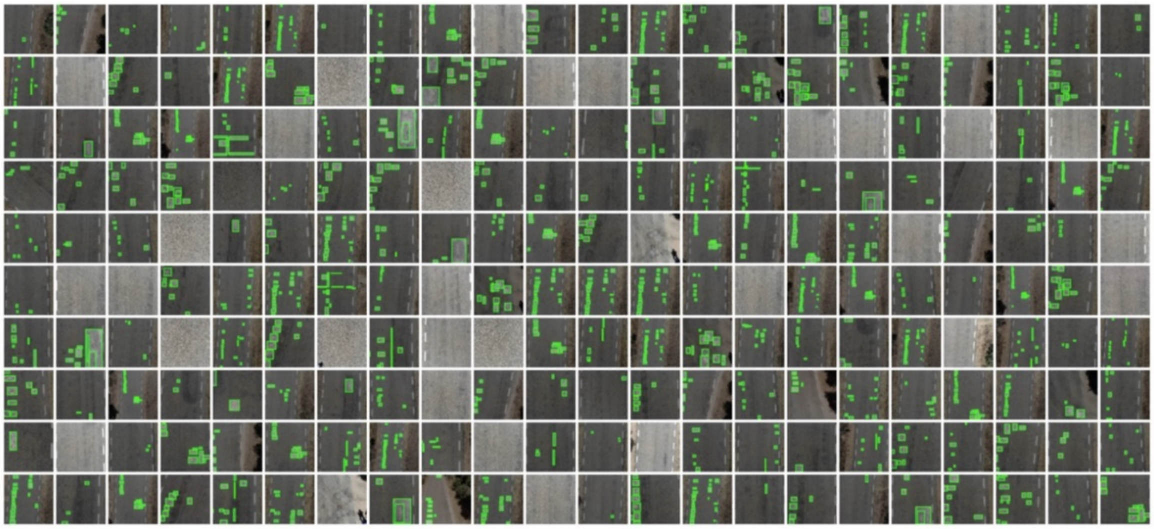

Figure 2: Sample images from the dataset [4] that contain UAV images for crack and pothole recognition.

3.3 Evaluation metrics

Regarding the detection task, we utilized the Intersection over Union (IoU), which is a popular evaluation metric used to measure the accuracy of an object detector on a particular dataset. It measures the overlap between the predicted bounding box and the ground truth bounding box for an object. To calculate the IoU, we first calculate the intersection of the predicted and ground truth bounding boxes. This is the region where the predicted box and ground truth box overlap. We then divide the area of this intersection by the area of the union of the two bounding boxes. The IoU score ranges from 0 to 1, and in general, a higher value indicates better object detection performance. The IoU metric is defined as follows:

$$IoU = \frac{TP}{TP + FP + TN} \tag{1}$$

where true positives (predicted correctly as positive) are denoted as TP, false positives (predicted incorrectly as positive) as FP, and false positives (predicted incorrectly as positives) as FP.

In parallel, regarding the classification task of the road defects on a given UAV image the performance of the implemented architecture is evaluated in terms of three metrics as follows: (i) precision, (ii) recall, and (iii) F1-score. Precision, also known as positive predictive value, measures the accuracy of the model's predictions and is calculated as seen in the following expression:

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

It is noted that precision is the ratio of correct positive outcomes to the total positive outcomes that the network considers and thus indicates how good a network is when its output is positive. A low precision score implies a high number of false alarms.

Similarly, recall, also known as sensitivity, measures how well the model predicts the total of positives and is calculated as seen in the formula below:

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

where false negatives (predicted incorrectly as negatives) are denoted as FN. It is underlined that recall is the percentage of correct positive outcomes to the total of positive cases in the ground truth, and, therefore, shows how many of the positive classes the network can correctly predict. A low recall score entails that the classifier has a high number of misses.

Finally, the F1-score is a combination of these two last aforementioned metrics and is described as the harmonic mean of precision and recall [28]. It is calculated as in the following expression:

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{4}$$

3.4 Experimental evaluation

The performance of the object detection task is illustrated in Figure 3(a) with a confidence level of 95% over the data of the test set. In parallel, the classification capabilities in terms of the performance metrics that were demonstrated in the previous section are shown in Figure 3(b-c). It is also noted that, regarding computational complexity, the model needs an average time of 0.059 seconds to identify the road defects on a UAV image.

Consequently, as illustrated in Figure 3, the proposed computer vision framework, which utilizes the YOLOv5 detector and drone images, can classify and localize as well as localize two classes of road defects (i.e., cracks and potholes), in the processed UAV imagery. The final network was able to demonstrate an IoU score of up to 95.64% for the detection task and an F1-score of up to 67.82% for the classification task with precision and recall scores of 52.83% and 96.15%, respectively.

3.5 Evaluation of the object detector on UAV images with cracks and potholes

In this section, we present the experimental results that the YOLOv5 model demonstrated during the evaluation process. More specifically, in Figure 4 one can observe the automated identification

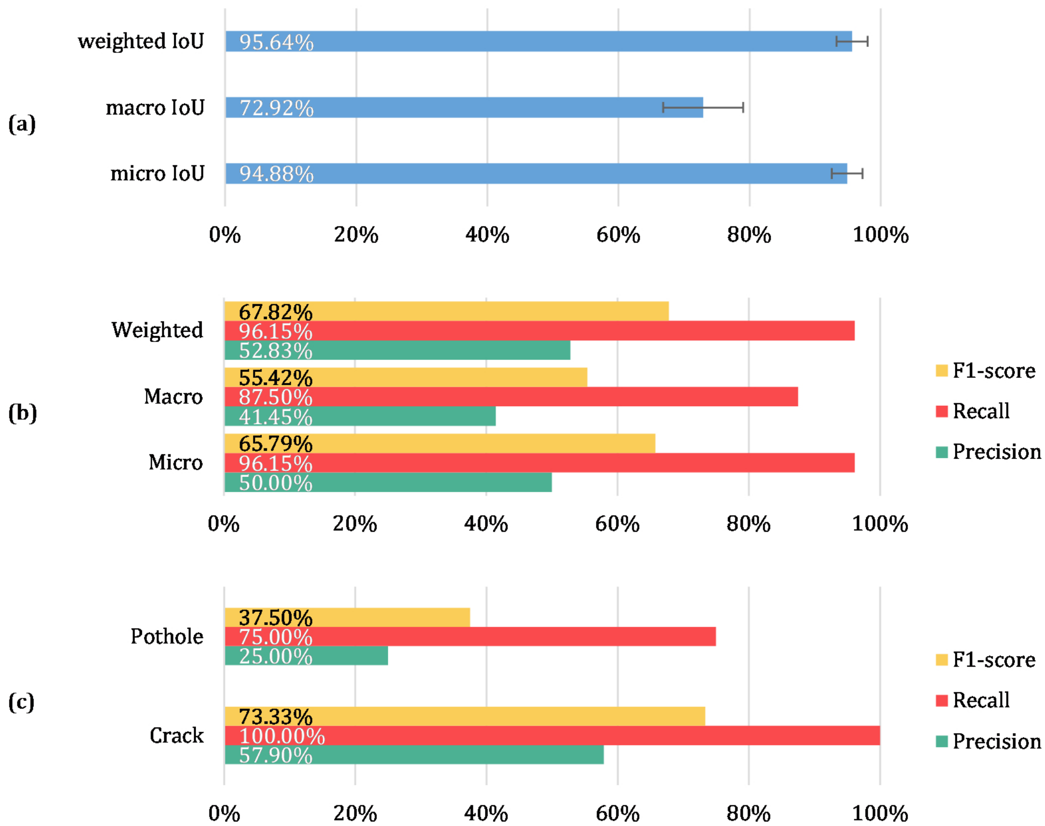

Figure 3: Average performance over the images of the test set of the dataset [4] in terms of (a) micro, macro, and weighted IoU scores, (b) classification scores calculated with micro, macro, and weighted averaging, and (c) classification scores calculated per class.

capabilities of the proposed YOLOv5 architecture in the automated crack and pothole detection task from UAV images. The aforementioned figure shows six indicative drone images of the test set and, in particular, the first column corresponds to the original RGB drone images followed by their ground truth bounding boxes in the second column. Finally, the third column shows the predicted bounding boxes with their corresponding confidence scores.

To effectively explore the performance of the model, the test images can contain (i) only cracks [e.g., Figure 4(a)], (ii) only potholes [e.g., Figure 4(b)], (iii) both cracks and potholes [e.g., Figure 4(c)], (iv) healthy asphalt surface without degradation [e.g., Figure 4(d)]. It is noted that the images are unseen data during the training process of the deep model. As one can see in the aforementioned figure, and in particular in the third column, the model showed satisfactory recognition and localization performance of the cracks and potholes. It is however noted that in rare cases the network failed to identify (false negative) a defect in the drone image [e.g., Figure 4(f)]. In parallel, in rare cases, the model misclassified an object (false positive) as a defect [e.g., Figure 4(e)]. Nevertheless, it is emphasized that the input data of the system is consecutive RGB frames of a video sequence, and, therefore, even if the detection fails for the current frame, it is highly likely that it will succeed in the next ones [29], [30], [31].

4 CONCLUSIONS

In conclusion, this paper has presented a YOLOv5 model for the detection of cracks and potholes in road surfaces using UAV images. The proposed model has demonstrated promising performance in terms of localization accuracy and speed, which is critical for the real-time detection and monitoring of road defects. The effectiveness of the proposed framework was validated using a real-world dataset of UAV images, and the results showed that it performed satisfactorily in terms of precision, recall, F1-score, and IoU metrics. To this end, the use of UAV images in conjunction with the YOLOv5 model provides a cost-effective and safe method of road inspection, reducing the risks and expenses associated with traditional inspection methods. Furthermore, the adoption of deep learning models for road defect detection can lead to more targeted and efficient road maintenance strategies, enhancing the safety and longevity of road infrastructures. In summary, the proposed deep network

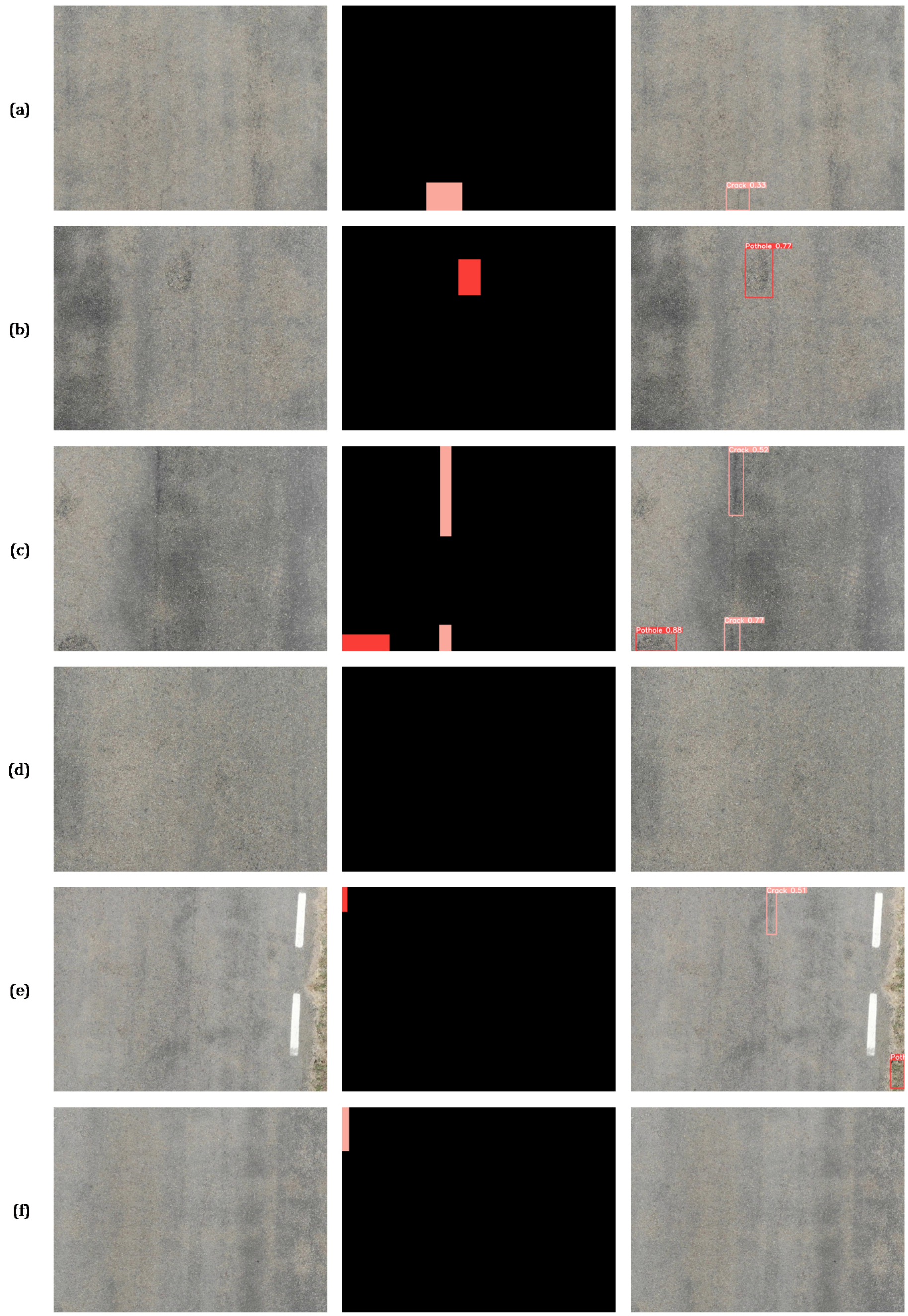

Figure 4: Automated localization of (i) cracks (pink bounding boxes) and (ii) potholes (red bounding boxes) on UAV images using a small YOLOv5 deep model trained and tested on the dataset [4].

can significantly improve road infrastructure monitoring as well as maintenance, and, thereby, can be a powerful auxiliary tool in the hands of civil engineers and road construction experts.

Future work can focus on exploring the integration of multi-sensor data and fusion techniques to improve the detection capabilities of the proposed framework. Combining UAV imagery with other sensors, such as LiDAR or thermal sensors, can provide complementary information for more accurate detection and characterization of road cracks and potholes. Thereby, by leveraging the strengths of different sensors, we can enhance the system's ability to identify and classify various types of road surface damage.

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