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Real-Time Concrete Damage Detection Using Machines Learning for High Rise Structures

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Abstract: The number of aging high-rise civil structures is growing throughout the world, and maximum of them use concrete as a building material and is also very important material. There are high chances of concrete lose its strength due to continuous loading and environmental impacts. There by, damage may occur on the exterior surface of the structure. Whenever these deformities are left without investigated and untouched, the integrity of the structure may be compromised. Therefore, regular maintenance of the structure is very much nessesary. Some of the prior studies have used a drone as a instrument to capture and record the current state of the structure. Later, captured videos and images should analyze all the pictures to determine damage using object classification, localization, and segmentation methods. Sometimes the drones relay the collected data which uses a wireless medium. However, the developed systems are very complicated, time consuming, and requires a very high bandwidth

Keywords: Crack detection, Concrete bridge deck, Machine learning Real Times

I. INTRODUCTION

Traditional crack-detection surveys of civil structures usually rely on visual examination techniques. High-rising civil structures, for example, towers, dams, residential buildings, industrial plants typically have an inaccessible area, which is difficult to inspect due to their shape With the rapid technological development of drones, the restriction of conventional visual inspection could be minimized by cutting edge damage monitoring

Drones is used to capture images in proximity to surface damage in real-world buildings, it enhances the results of damage identification. Several digital image processing approaches have been employed for extracting the damage information efficiently from images and videos. For example, crack detection using edge detection and particle filter was used in paper and morphological techniques were studied in paper for automatic surface crack detection. Histogram analysis technique for crack detection was studied in paper isn the paper the authors tried various crack detection techniques, such as tensor voting, fractal method, edge detection, percolation, etc

Resently machine learning and deep learning techniques are getting a lot of recognition over conventional digital image processing techniques for concrete surface damage detection in drone-based applications. For example, the identification of pavement cracks and potholes was studied using a Support Vector Machine (SVM), a neural network, However, as per our knowledge, drones/UAVs are being used as a vehicle to capture images and videos of the exterior surface of the civil structure. Later, captured data is processed using digital image processing and artificial intelligence-based techniques to find out the damage. In certain studies, the captured data is also continuously transmitted to a server that resides on the ground through a wireless medium

II. RELATED WORK

Cracks and spalls detection in high-rise structures is the need of the current time. Starting from a small home to urban areas with skyscrapers, there is a propensity to detect early damage. In this section, we are reviewing the various current methodologies suggested by the authors. Digital Images processings has been implemented as an alternative to visual inspection for automated concrete damage evaluations. Several DIP approache have been employed to efficiently collects damage informations from images and the videos. For example: In paper [6], the authors proposed a method of crack detection by installing an embedded computing platform (Raspberry Pi, FPGA board) on UAVs. They used two algorithms which are used: segmentation by edge detection and crack detection using a particle filter. Later they compared the performance of these algorithms by executing them on various embedded computing platforms as well as on the desktop system. Paper [14] demonstrated UAV-based cracks detections and evaluations using image processing methods. Authors have mounted Raspberry Pi with a Wi-Fi modules, an ultrasonic distance sensor, and a camera on the AR Drone

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2.0 for crack image acquisition. These images were later processed using a digital image processing approach. Authors [15] have provided a UAV-based digital images processing prototypes for the detection of concrete crack. They used Raspberry and challenging for images with high variations in lighting and exterior surface texture. Some Machine learnings (ML) algorithms, such as Random Forests (RF), Support Vector Machine (SVM), and an Artificial Neural Network (ANN), have been implemented into automated concrete surface damage detection in recent years as Artificial Intelligence (AI) has advanced. Paper [1] emphasizes the identification of pavement damage (cracks & potholes). In which authors use UAVs to capture multispectral images of the pavement. In addition, machine learning algorithms such as SVM, Neural Networks , Random Forest have been used to differentiate between the regular pavements and the damaged pavements. In the paper [19], the authors proposed a UAV-based crack identification method for continuously observing rigid pavement conditions. They used SVM to classifying the crack images, and UAV was used to collect images of a rigid pavements. Authors [10] classified the different form of wall surfaces damage using SVM and the least squares SVM and used steerable filters and projections integral for the successful extraction of the features.

III. PROPOSED SYSTEM

A desktop machine with a configuration of CPU i7-2600 (3.40 GHz), RAM 8 GB, GPU NVIDIA TitanXp (12 GB) is used to train the YOLO family models. Also, the supporting libraries that make them easier to run YOLO-v3 and TYOLOv-3 including CUDA 10.0 toolkit with the cudnn 8.0, and OpenCV on Ubuntu 16.04 LTS (64 bits) operating system are installed. The proposed YOLO family models are implemented using the Darknet framework. The train- ing section is split into 2 phases. In the first phase, both models are trained and tested one by one on a desktop system equipped with a TitanXp GPU. Therefore, two classes named ‘‘spall’’ and ‘‘crack’’ have been developed. The crack class contains images of four different types of cracks (Vertical Crack, Horizontal Crack, Diagonal Crack, and Branch Crack). The datasets for this purpose consists of 400 images of various types of cracks (100 images of each type of cracks) and 400 images of spalls. Figure 6 depicts the dataset for training and testing. First, both models have trained with a 0.001 learning rate on varying input image sizes (608 608, 480 480, 416 416, 320 320, 224 224) one after another, and the corresponding trainings time and inference time is recorded (Table 4). The YOLO-v3 training is completed up to 4000 iterations for all image sizes with an average loss of less than 0.17. Similarly, TYOLO v3 training is terminated after 5000 iterations for all images sizes, and the average loss is reduced to less than 0.78. Furthermore, both models are trained and tested using different learning rates (0.002, 0.003, 0.004, 0.005), particularly with 608 608 image size. Figures 7 depicts the training losses (Total Loss & Avg. Loss) of both the models at 0.001 learning rate with varying input image sizes. The YOLO-v3 achieves the highest overall accuracy (77.22%) at a 0.001 learning rate and 608 608 input image size. In the same way, with a learning rate of 0.002 and an input image size of 608 608, TYOLO-v3 achieved the best performance (31.11% Overall Accuracy). Further more , no image resizing or augmentation is performed at any step, YOLO family models handle it automatically.

In the second phases, the YOLO family models are imported on the Jetson-TX2, which is equipped with a Pascals family GPU. There after, all object files are removed and the models is recompiled using the make files so that objects files compatible with the Jetson-TX2 can be created. In this case, both models are run with pre-trained weights to make predic tions on the test set, and the corresponding inference time is recorded.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FP}$$

$$Precision = \frac{TP}{TP + FP} \text{ or } \frac{TN}{TN + FN}$$

$$Recall = \frac{TP}{TP + FN} \text{ or } \frac{TN}{TN + FP}$$

$$Overall\ Accuracy = \frac{+}{TP + FP + TN + FN}$$

IV. PSEUDO CODE

Step 1: Generate all the possible route.

Step 2: Calculate the TE_{node} for each nodes of each route using equations(1).

Step 3: Check the below condition for each route till no route is available to transmit the packets.

if (RBE < = TE_{node})

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Make the node into sleep mode.
else
Select all the routes which have active node
ends
Step 4: Calculate the total transmissions energy for all the selected route using equation (2).
Step 5: Select the energy efficient routes on the basis of min total transmission energy of the route.
Step 6: Calculate the RBE for each nodes of the selected routes using equations (3).
Step 7: go to steps 3.
Step 8: Ends.

V. CONCLUSION AND FUTURE WORK

In this study, a multi-drone-based real-time damage detection system (DDS) for high-rise structures is proposed. The appropriate of the DDS, which is fitted with the camera for fields structure inspection uses, is also investigated. This system uses the YOLO family deep learning models to classify and localize damage in real-time. The DSS system hardware includes a drone based on a Pixhawk flight controller, a Logitech camera, Nvidia Jetson-TX2 with a built-in Wi-Fi module to provide a platform for capturing images, computing power for continuous algorithm execution and communication. Our system has superseded all of the previous systems discussed in the literature section of this paper in terms of real-time damage detection, network bandwidth saving, and reliability.

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BIOGRAPHY

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