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DETECTING CRACKS IN CONCRETE BASED ON IMAGES USING AMAZON WEB SERVICE REKOGNITION

Roman Mysiuk[1], Volodymyr Yuzevych[1,2], Iryna Mysiuk[1], Ihor Ohirko[1,3]

[1] *Department of System Design,*
Ivan Franko National University of Lviv
50 Drahomanova St., UA-79005 Lviv, Ukraine
mysiukr@ukr.net

[2] *Department of Electrophysical Methods of Non-Destructive Testing,*
Karpenko Physico-mechanical Institute of the NAS of Ukraine
5 Naukova St., UA-79601 Lviv, Ukraine

[3] *Department of Information Multimedia Technologies,*
Ukrainian Academy of Printing,
19 Pid Holoskom St., UA-79020 Lviv, Ukraine

Concrete is the basis for many structures in architecture and infrastructure. Under the influence of external factors and load from use, this material can be destroyed. At first, microcracks may form in the concrete, which grows into larger cracks over time. Detection of such cracks can be performed with the help of information technologies. Cloud technologies are gaining popularity today. Among the largest service providers in this direction is Amazon Web Service. There are many opportunities in this cloud environment for computing using artificial intelligence. In the work, the recognition of cracks in concrete is performed using the Amazon Web Service Rekognition. The images with the concrete crack and the corroded pipe are analyzed for label matches. Based on the given test and training images with defects, cracks are recognized using Amazon Rekognition Custom Labels. The main elements of the image are identified, namely concrete and cracks. As a result, the described recognition method can be used for the automatic detection of defects in concrete.

Keywords: machine learning, concrete, crack, bounding box, label, cloud technologies.

Overview

Concrete is the basis of many building structures. The durability of this material depends on external influences such as soil moisture, weather conditions, and operational loads. Cracks may appear in concrete under the influence of these factors. The state of concrete for the presence of a crack can be monitored using convolutional neural networks [1], image processing [2], a modified spectral clustering method [3], the possibility of using YOLOv5 software library [4], or the creation of deep learning models [5]. There are few works dedicated to using the capabilities of cloud environments.

Today, there are already many ready-made solutions that help simplify the work of the developer. The most universal way to access data and applications from anywhere on the planet is the Internet. The web browser is used to access the required resource as a client. Cloud environments can be used as an alternative to real computers. One of the services that contain many functions in one service provider is Amazon Web Service (AWS) [6].

Despite the possibilities of data storage and the creation of separate computing clusters in cloud environments, there are opportunities for working with data and machine learning [7].

To determine the algorithm by which machine learning will take place in this cloud environment, there is an automated machine learning (AutoML) mechanism [8]. This feature can automatically fill in some missing data, adjust models, and train machine learning. In addition, AutoML can determine the type of predictions that best fit data, such as binary classification, multiclass classification, or regression. Among the available algorithms, AutoML can choose the most effective ones from feedforward deep neural networks, gradient-boosting decision trees, and logistic regression. It is possible to automatically determine the algorithm from the model that is most suitable among others.

The work used recognition based on Personal Protective Equipment (PPE) [9] and Label detection [10]. Object labeling is applied to the ability to identify certain objects in an image. Especially, this is used for raw data in an image or video. Labeled data is used in model training to assign a certain class to an object in an unclassified array of data. Moreover, one image can have several labels. This algorithm uses semantic segmentation, which is the process of working with image pixels. To create a separate training set, it is necessary to manually specify the boundaries of the objects in the image. Using the bounding box, detected objects are displayed based on four coordinate points. The object training process continues until the discrepancy between manually entered and automatically corrected labels decreases below a desired threshold.

Similar detection capabilities are available in other large cloud environments such as Google Cloud Platform (AutoML Vision) and Azure (Machine Learning Data Labeling).

The purpose of the work is to investigate the possibilities of using the AWS cloud environment with the Rekognition function to detect cracks in concrete.

The following main tasks can be identified in this work:

1. Explore the capabilities and basic methods of image-based object detection in the AWS cloud environment

2. Detect damaged road elements based on the image of cracked concrete using the method of creating custom labels in AWS Rekognition.

The result of image-based object detection

Among the possible options for recognizing objects in an image in Amazon Web Service, there are the following possibilities:

- *Label detection* – automatic detection of objects with signatures and the corresponding confidence score
- *Image moderation*. This type of recognition detects image content for bad habits and inappropriate information for certain age groups of people.
- *Facial analysis* provides an analysis of the face and indicates a confidence rating
- *Celebrity recognition* recognizes the faces of famous people
- *Face comparison* allows you to establish the similarity of faces
- *Text in image* recognizes the text in the image and outputs the text
- *PPE detection.* Personal Protective Equipment recognizes people and their body parts

For example, Figure 1 shows the result of detecting parts of a person welding a damaged pipeline using PPE detection. Besides the visualization, API (Application Program Interface) queries and responses are also available in the results. The request contains information about the name of the figure, and the response contains information about the detected human body parts with a confidence value, and a bounding box around the detected object. Most of all described options are available in demo versions, but there is a possibility to create custom detectors in the AWS cloud environment.

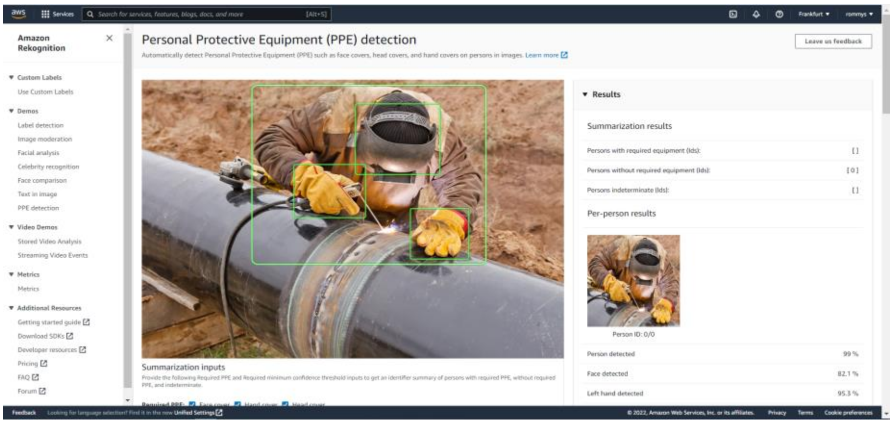

Fig. 1. PPE detection of pipe welder

Since it is possible to upload your own photo for object detection, a photo of a pipe welder with his hands and face covered is chosen. In this case, the detection of body parts becomes difficult due to the changed shape of the objects.

As a result, the following objects have discovered a person with an accuracy 99 %, the face of a person with an accuracy 82.1 %, the left hand - 95.3 %, the hand cover detected on the left hand - 92 %, and the right hand - 95.4 %.

Another detection capability is label-based recognition. At that time, the results of the faded labels appear on the right side of the screen. For example, Figure 2 shows a crack in a concrete base.

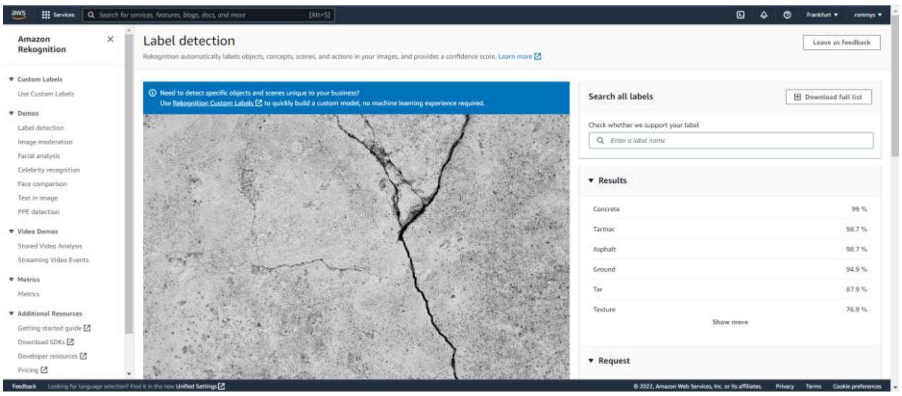

Fig. 2. Label detection of concrete image

The result of detecting the main features in the image based on the labels showed quite good results. The most relevant words of the image are found, such as concrete (confidence 99%), tarmac or asphalt (98.7%), ground (94.9%), tar (87.9%), texture (76.9%), and floor (58.7%).

Similarly, as in the previous case, it is possible to check JSON (JavaScript Object Notation) API requests and responses as it is shown in Figure 3. The API request contains a stream of image bytes. The response contains several entities with information to display, namely label name and confidence. In addition, the parent label associated with the current one is displayed.

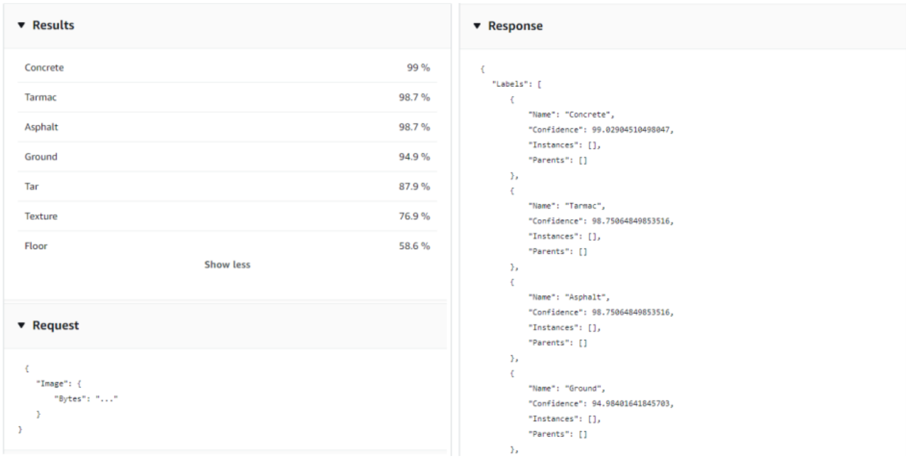

Fig. 3. Result, request, and response to API in AWS Rekognition label detection

However, there are limits in the tag detection algorithm on the number of words that can be tagged. A search string can be used to find expected tag values, or a file can be downloaded from the tag list. The classified label file contains 2580 words and 258 labels with bounding box words. These data are contained in two CSV (Comma Separated Values) files, respectively, which can be downloaded directly from the web page. This is the result of some words being missing from the list of available defined words. As you can see, in Figure 2 with the defection of cracks in the concrete, the "crack" label is not found.

For a more detailed examination of the tag detector, an image has been uploaded to AWS with a corrosion pipe. Figure 4 shows that the list of words has been detected and some objects have been highlighted with labels and bounding boxes. As a result, the following labels are detected from the image with a confidence value: rust (99.7%), lizard (80.2%), animal (80.2%), reptile (80.2%), painting (77.6%), art (77.6%), wood (72.9%), handrail (59.4%), and banister (59.4%). Some of these words may not exactly correspond to the image used, but the tag "rust" is shown correctly. The indicated words may be associated with a limited number of labels and image coloring. The image has "Painting" and "Lizard" bounding boxes highlighted. It can be observed from the API response received by JSON that the words reptile and animal are parent words to the word "Lizard". That's probably why these words appear in the list of results.

In general, it can be considered that such detection can be used for surface recognition of materials. It is worth paying attention to the labels with the highest confidence value to draw conclusions.

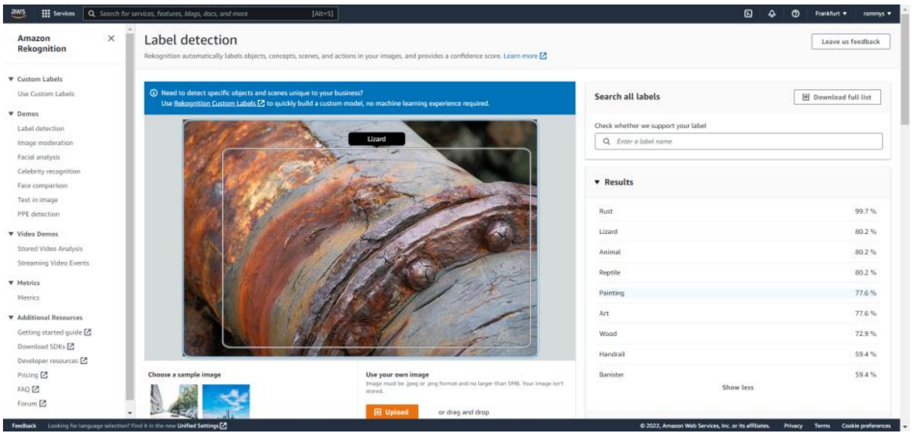

Fig. 4. Label detection of corrosion pipe

The next step is to highlight the area where the word "Lizard" is found in Figure 4. In Figure 5 the same area is highlighted with a "Painting" bounding box. In addition, the following labels are found wood (99.2%), rust (94.9%), rock (93.6%), slate (84.4%), painting (55.8%), and art (55.8%).

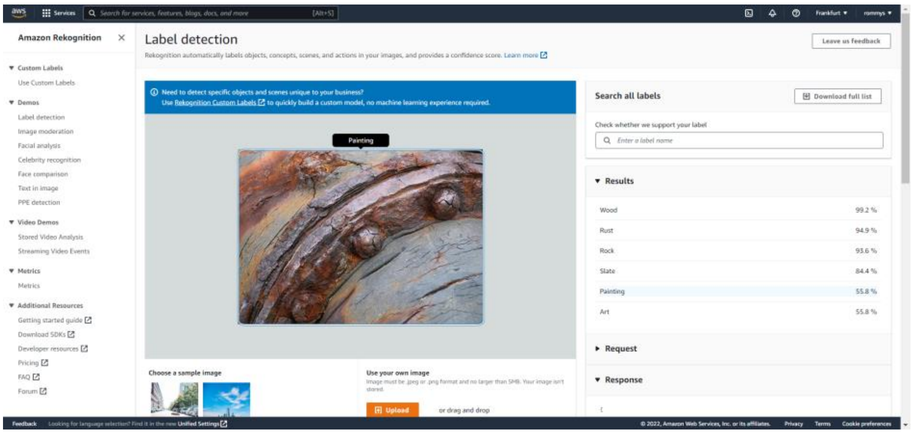

Fig. 5. Pushing test data to Elasticsearch

These results may be limited to the demo version, a more comprehensive analysis requires research for custom labels. The obtained results can be useful for analyzing a certain defined set of images and finding common characteristics and coincidences between them. It can be assumed that in this case, it is possible to analyze the results of the black box since the execution process takes place in the API and there is no direct access to the program code. But on the other hand, it allows you to concentrate on the obtained results by not including all the details of the learning process and the use of machine learning for users.

The result of custom labels for recognizing cracks in concrete

In the AWS cloud environment, it is possible to create your own custom labels for recognition, which is called AWS Recognition Custom Labels. This capability is more persistent due to the learning process in the process of establishing relationships between expected and training labels.

A good option is to try these features for free for three months. However, there are limitations to the 4 inference hours during which the main metrics and training results are formed. Limitations also apply to training time of up to 10 free hours.

The training process for recognizing details in images can be divided into the following stages: creating a dataset, placing labels on images in the training and test sets, training the model, and analyzing the results. In the first stage, when creating a model, it is necessary to determine how the data set is distributed. Possible options include splitting one common data set into 80% training data and 20% test data or forming separate training and test data sets. In this work, the second method is chosen, as it is recommended for most users. In addition, in the second case, there should be a greater opportunity to control the learning process and tune the received recognition performance metrics.

Initially, the test set is formed based on a small number of images. For the learning process, 21 training images and 3 test images are loaded into the environment. All files are stored in S3 bucket storage [11] as shown in Figure 6.

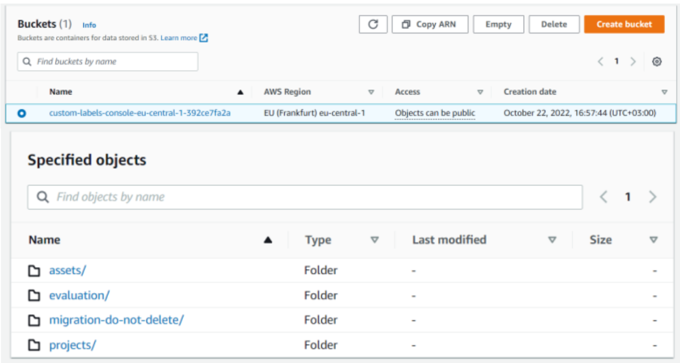

Fig. 6. S3 bucket and the folder structure with saved images

The next step is to determine the selection labels based on the test data of the areas that correspond to these words. Two training and test labels with the words "concrete" and "Crack" are defined. Figure 7 shows the main extractions, respectively, for labels based on 6 training images. In the same way, 1 test image is selected for the selection of expected identification objects as it is shown in Figure 8. Only 6 images out of 21 are selected initially as an attempt to review the results for further improvement.

The labeling stage is important because the time of training and its result depends on the accuracy of the selection. Moreover, this process has the following sequence: creating word labels, placing them on images, and drawing selected areas of objects according to the labels. The website is designed in such a way that it does not allow you to perform the wrong sequence of described actions.

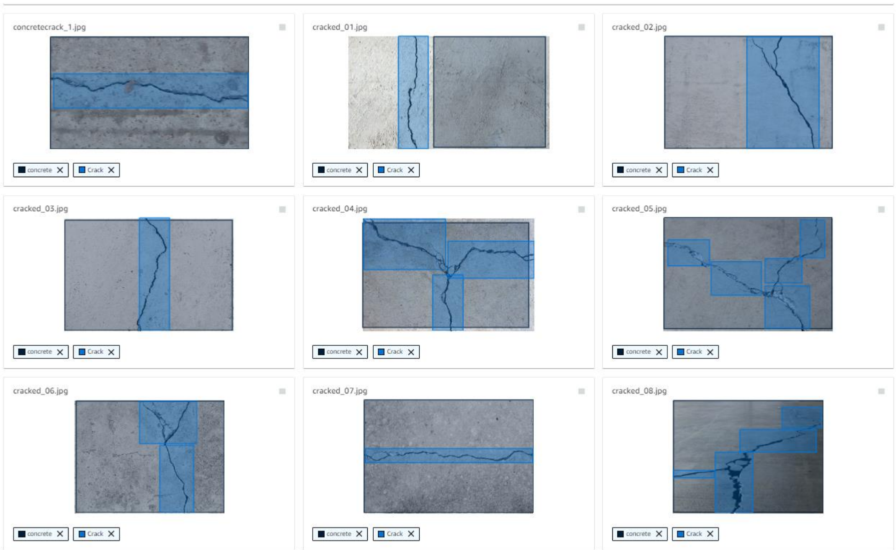

Fig. 7. Applying labels to test images with selected areas of crack and concrete

As shown in Figure 8, a real part of a concrete road with cracks is taken as a test pattern. There are also other elements in the picture, such as bushes and trees, which should not be recognized.

Fig. 8. Applying labels to training images with selected areas of crack and concrete

Also, with the combination, it is not possible to perform training with an erroneous message that there is less than a 50% overlap of valid labels between the training and testing manifest files.

After that, all selected cracks as labels and selected areas for them are removed. A different image from the test data is selected to identify only the concrete in the image. The training results for concrete detection are shown in Figure 9. The concrete in the figure is determined with a confidence of 68.5%. The recognition result can be considered quite good. Other elements such as bushes and trees are not found except concrete. The result is obtained after training for an hour. Moreover, in this case, the same 1 test and 6 training data are used, but without cracks.

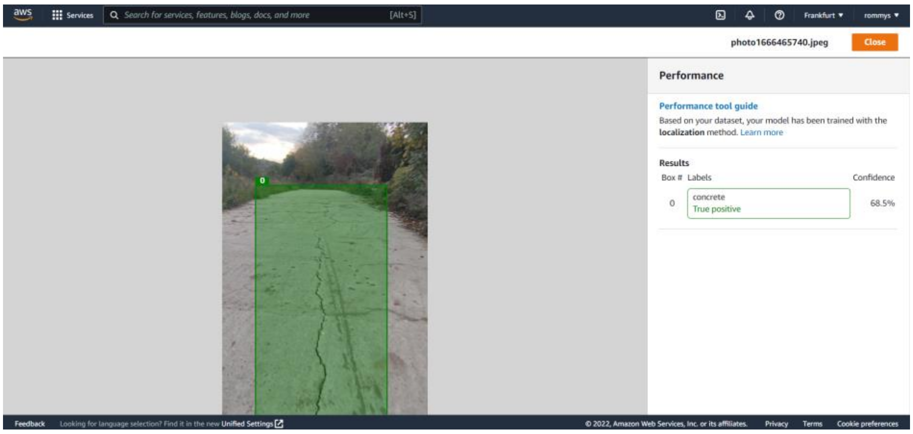

Fig. 9. Detected bounding box of concrete

One assumption is that not enough test images are selected. Therefore, for all 21 images, labels are placed on concrete and cracks with the selection of the corresponding areas. In this case, even small areas with damage to the road surface are marked. In addition, as shown in Figure 10, the expected areas with cracks and concrete are marked with labels for one of the training execution.

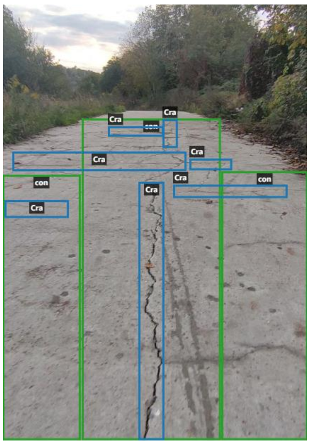

Fig. 10. Setting the expected areas for concretes and cracks for one of training executions

In the next execution of the training run, the same areas as in Figure 10 with labels are taken, only instead of 3 areas of concrete, one general area is chosen. The number of marked cracks for determination is 7. As we can see in Figure 11, only one crack is detected out of all the marked ones and all the rest of the detections relate to concrete. The recognition is not entirely accurate. However, it made it possible to draw certain conclusions and tune the labels for further experiments. It seems that the number of cracks is large, and the number of test models is insufficient.

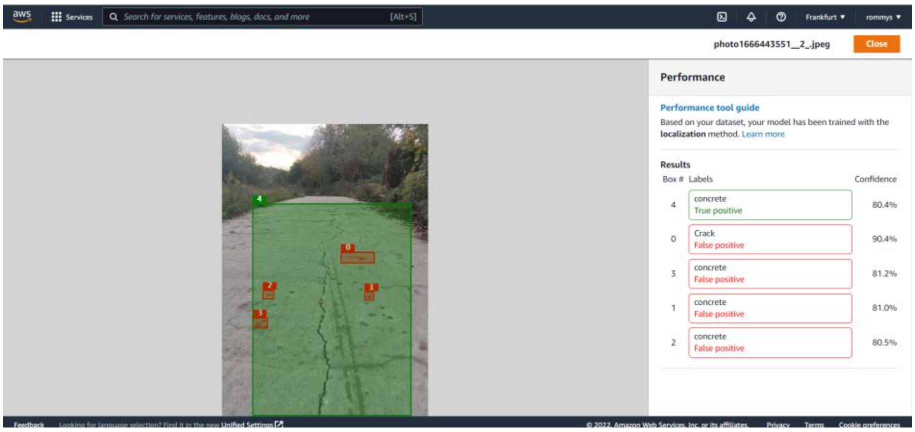

Fig. 11. Detected bounding boxes based on 21 training images

A larger amount of labeled test data is selected for the next run. 19 more images from different angles of cracks from a similar area are added to the 21 test data marked with labels. As can be seen in Figure 12, the concrete is detected, but the cracks are not in all areas and not exactly. In many places, it is expected that the crack mark instead contains concrete.

Fig. 12. Detected bounding boxes based on 40 training images

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The reason for not quite accurate recognition can be many small details of cracks that are expected to be detected. The learning process turned out to be successful when the more common and largest cracks in the concrete are selected. The test data sets remained unchanged, only the expected highlighted labels in the test image changed. As we can see in Figure 13, the detection result turned out to be much better and more accurate.

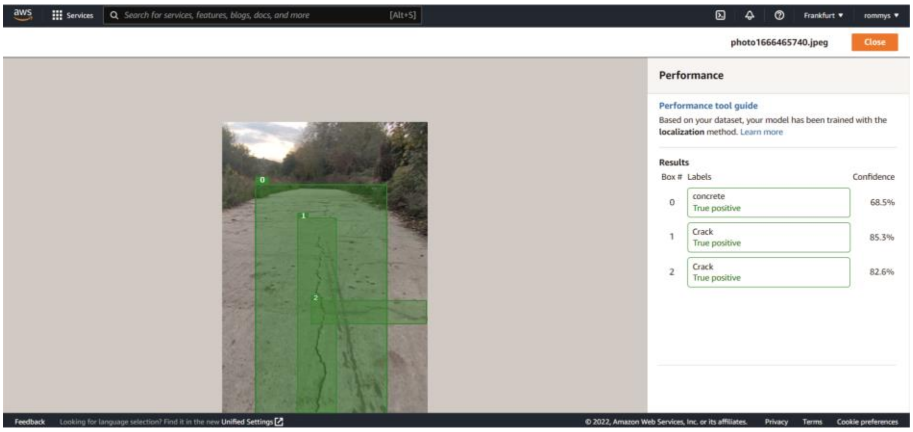

Fig. 13. Detected bounding boxes with recognized cracks and concrete

Metrics displayed after each run can be used to improve training results. For each label, the described values are calculated and displayed in the form of a table. The model evaluation results include the following indicators [12]:

- Average precision that indicates how much true positives predictions over all predictions
- Overall recall means how many labels are predicted correctly
- F1 score collects evaluation of precision and recall values
- The predicted threshold value contains the prediction for the considered a true or false positive.

In general, this method of detecting cracks in concrete can be used to analyze a section not only of a concrete road but also of other types of roads.

Conclusion

Concrete is a stable material, but under the influence of various external factors, it can be destroyed. One of the types of defects in this material is cracks. Object recognition and detection allow you to detect certain details in an image automatically after the learning process. The paper explores the possibilities of using machine learning in combination with computer vision to detect cracks in concrete.

In the cloud environment of Amazon Web Service, the dependence of the change of label detection on the image is investigated based on the example images. The accuracy of the determination with the confidence value is quite high. In addition, due to the limited number of labels, some additional words do not match the image.

Models for own objects can be created using the detection method based on custom labels. The paper describes the process of creating and training a model for detecting cracks in concrete. As a result, the capabilities of the Amazon Web Service Rekognition functionality are shown. This tool allows you to conduct research on the detection of objects and establish certain dependencies between the obtained model performance indicators on a more visual level.

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ВИЯВЛЕННЯ ТРІЩИН У БЕТОНІ НА ОСНОВІ ЗОБРАЖЕНЬ ВИКОРИСТОВУЮЧИ AMAZON WEB SERVICE REKOGNITION

Роман Мисюк [1], Володимир Юзевич [1,2], Ірина Мисюк [1], Ігор Огірко [1,3]

[1] *Кафедра системного проектування,*
Львівський національний університет імені Івана Франка,
вул. Драгоманова, 50, Львів, 79005, Україна
mysiukr@urk.net

[2] *Фізико-механічний інститут ім. Г. Карпенка НАН України,*
вул. Наукова, 5, Львів, 79601, Україна.

Кафедра інформаційних мультимедійних технологій,
Українська академія друкарства,
вул. Під Голоском, 19, Львів, 79020, Україна

Бетон є основою для багатьох конструкцій в архітектурі та інфраструктурі. Під впливом зовнішніх факторів і навантаження від експлуатації цей матеріал може руйнуватися. Спочатку в бетоні можуть утворюватися мікротріщини, які з часом переростають у великі тріщини. Виявлення таких тріщин можна здійснити за допомогою інформаційних технологій. Хмарні технології сьогодні набирають популярності. Серед найбільших постачальників послуг у цьому напрямку – Amazon Web Service. У цьому хмарному середовищі є багато можливостей для обчислень із використанням штучного інтелекту. Також за допомогою вбудованого механізму автоматичного машиного навчання дає змогу швидко налаштовувати та отримувати результати після навчання для подальшого аналізу.

У роботі розпізнавання тріщин у бетоні виконується за допомогою Amazon Web Service Rekognition. Проаналізовано можливості виявлення об’єктів на зображеннях за допомогою Personal Protective Equipment та Label Detection. Крім цього, описано інші можливості проведення розпізнавання на основі готових до використання моделей для різних об’єктів дослідження. Personal Protective Equipment може застосовуватися для виділення головних частин тіла людини. При чому таких спосіб можна вважати ефективним для розпізнавання навіть при наявності закритих частин тіла. Зображення з бетонною тріщиною та корозійною трубою були проаналізовані на відповідність міткам. Встановлено основні залежності між мітками та вмісту зображень.

На основі наданих тестових і тренувальних зображень з дефектами тріщини розпізнаються за допомогою спеціальних міток Amazon Rekognition. Визначено основні елементи зображення, а саме бетон і тріщини. Описано процес налаштування міток та навчання у веб сторінці. У процесі кількох виконаних ітерацій навчання протестовано зміну кількість міток та величину виділених рамок об’єктів. Проаналізовано співвідношення залежності кількості тестових та тренувальних зображень для кращого розпізнавання. В результаті описаний метод розпізнавання можна використовувати для автоматичного виявлення дефектів у бетон чи інших матеріалах.

Ключові слова: машинне навчання, бетон, тріщина, виділена рамка, мітка, хмарні технології.

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