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Implementation of Computer Vision technique for Crack Monitoring in Concrete Structure

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Abstract - Assessment of structural health is essential for safe and efficient functioning of built environment. Physical inspection of structures for its health monitoring is time consuming, costly and risky. Advances in image capturing and processing techniques as well as numerical simulation tools have made computer vision a cost effective and accurate alternative for structural health assessment. Evolution of convolution neural network (CNN) has reduced human effort and made it easy to develop algorithms for identification of structure defects. One of the primary defects in concrete is crack. Concrete cracking occurs due to many reasons like shrinkage, heaving, premature drying, excessive loading etc. and it leads to reduction in strength of structures. This paper presents a computer vision system developed for crack monitoring of concrete cubes subjected to compressive loading. Camera is used to capture real time images when concrete cubes are subjected to loading. Images are further processed using CNN to obtain various features of cracks like numbers, location, length, area etc. Present Computer vision system is developed using LabVIEW and implemented using tensor processing unit (TPU) for better computational efficiency. The outcome of present system demonstrated better and accurate real time monitoring of cracking when concrete is subjected to loading. Proposed computer vision system can be implemented for structural health monitors of real-life civil engineering structures like buildings and bridges.

Keywords - Artificial intelligence; convolution neural network; computer vision; digital image processing; concrete crack detection; structural component health monitoring.

INTRODUCTION

Concrete is one of the widely used construction material, made of various cementitious materials and aggregates. There can be several causes for failure of concrete. Cracking in concrete indicate deterioration in strength and warn against possible failure. Physical inspection of concrete structures and crack monitoring help in assessment of strength. In alternate to physical inspection, images of critical locations can be captured by cameras and processing of images gives data about current condition of structures. With the proper interpretation of collected data and artificial intelligence, residual strength of structural elements can be predicted and if required, they can be strengthened for increased life span of structure. This technique doesn't need any equipment rather than visual input equipment so it is easier and economical to identify cracks. Generally concrete contribute major strength in compression and steel reinforcement is used for satisfying tension strength requirement of structure.

Artificial intelligence (AI) is a broad term for the simulation of human intelligence in computers. Artificial Intelligence is the capacity of computers to think and behave in the same way as humans do. Machine learning and deep learning are two subcategories of AI. Machine Learning is the branch of Artificial Intelligence that allows a machine to learn on its own without having to be specifically programmed. There are a variety of machine learning algorithms that evaluate the data and generate a function to predict an output based on the new inputs.

In 2003, Hung and Voloshin [1] developed a fast and simple (FAS) detection algorithm based on digital image correlation (DIC) for measurement of the surface deformation of planar objects. The concept of finite element method (FEM) was applied by Sun et al.[20] to determine the complete, two-dimensional displacement field during the image correlation process on digital images. They used both numerical studies and a real experiment to verify the proposed formulation and showed that the image correlation with the finite element formulation is computationally efficient, accurate, and robust. In 2006, Besnard [12] et al. introduced the concept of multiscale approach on top of FEM based DIC method to generate meaningful solution for a fine texture and large initial displacement measurement. In 2011, Nguyen et al. [13] developed a new automated method of fracture identification and quantification based on standard DIC approach. An automatic crack detection system was proposed by Zhang et al. [14] by employing a coarse-to-fine methodology that also included concepts like Region of Aggregation (ROA) and Region of Belief (ROB) for segmentation and localization of cracks. Chambon and Moliard [19] proposed a new approach to image-based crack detection, GaMM, based on a multi-scale extraction and Markovian segmentation, which reduced the percentage of false positives in comparison to morphological methods that combine thresholding and refinement by morphological analysis. Xie et al. [15] demonstrated the potential for Deep Learning based pavement crack detection by applying ConvNets on a dataset of 500 images of size 3264 × 2448, collected using a low-cost smartphone. Ying and Salari [16] proposed a beamlet transform-based technique for pavement crack detection and classification, which was more robust in extracting linear features in the presence of noise. Oliveira and Correia [17] proposed an integrated system, CrackIT, for automatic detection and characterization of cracks in flexible pavement surfaces using a combination of unsupervised learning (clustering) followed by supervised learning (classification), thus eliminating the need for manually labelling the samples. It was noted that although CrackIT was able to detect multiple cracks in the same image, it had difficulty in dealing with cracks less than 2 mm width. Based on the fact that crack pixels in pavement images had distinct grayscale intensities compared to their surrounding non-crack pixels, Cheng et al. [18] proposed a pavement crack detection algorithm based on fuzzy logic. Feng et al.[21] proposed a deep active learning strategy for civil infrastructure defect detection and classification, where they used a deep residual network (ResNet) to train a small set of images with defect labels and use this low-accuracy defect detector to filter out many non-defect images.

The ageing civil infrastructure (e.g., tunnels and bridges) is a common problem in many developed countries such as the United States and Japan. According to (ASCE 2013), one ninth of the 607,380 bridges in the U.S. were structurally deficient and required a $20.5 billion annual investment for fixing the problems by 2028. While in developing countries like China and India, more civil infrastructure is being built. To efficiently monitor and maintain such a large number of existing civil infrastructure is critical yet challenging for both safety and economic reasons.

This paper presents application of computer vision technique for crack identification in concrete cubes subjected to compressive loading. The developed system includes camera for image capturing, CNN for crack identification from captured images implemented through LabView and TPU. The presented system can be easily implemented for real time monitoring of concrete structures.

Crack detection methodology in proposed system

Deep learning refers to the process by which computers can imitate human behaviour. They make use of neural networks, which are multi-layered systems inspired by the human brain's structure. One of the most popular image recognition algorithms used in deep learning is the convolutional neural network. It takes an image as input and processes it so that different aspects of the image can be distinguished from one another. They use artificial neurons, which are mathematical functions that measure the weighted number of multiple inputs and outputs an activation value and are modelled after neurons in the human brain.

The conventional image processing method does not work well in the detection of cracks in concrete structures as the intensity range of cracks and non-cracks in the concrete block is almost similar. Further, as the load increases on concrete specimen, the area of the crack increases and it merges to become a longer crack so, area-based filtering of the non-crack block is quite challenging. CNN improves this task by combining the output of different trained convolutional networks in a fusion multi-Layer perceptron and the features present in the feature map extracted by the convolution layer are summarized by the pooling operation.

A. Convolutional Neural Network

Convolutional Neural networks, also known as ConvNet or simply CNN, are a deep learning algorithm, which mainly finds its applications in visual imagery tasks. It can take an image as an input and can identify and differentiate

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various features from it. The Convolutional Neural networks were inspired by the human brain and have a structure analogous to the neuron connectivity pattern in human brains. They are composed of multiple layers of artificial neurons, which are mathematical functions that calculate a weighted sum of inputs and outputs a possibility score or activation value.

1) Architecture of CNN: The convolutional neural networks have many layers and try to extract different features from the input image. The starting layers try to find basic features and the complexity increases as we go deeper into the network. Each layer has three dimensions, height, width and depth.

2) Convolutional Layers: The convolutional layers try to find the high-level features from an input image such as edges. These are the starting layers of a convolutional network and there can be more than one convolutional layer in the network. They start by extracting the low-level features such as edges, color, etc. and as we go deeper to other convolutional layers, the network adapts to extract more complex features.

3) Pooling Layer: The pooling layer tries to reduce the spatial size of the convolved feature to reduce the computational power required. It also extracts the more dominant features, that are invariant to rotation and position. Pooling is of two types, Max Pooling, and Average Pooling.

4) Max Pooling: It returns the maximum value from the portion of the image covered by the filter.

5) Average Pooling: It returns the average value.

6) Classification Layer: The classification layer, also known as the Fully Connected Layer, are the final layers of the convolutional network in which the output of the pooling layer acts as the input and uses a SoftMax function to calculate the final possibility probabilities of the input. Complete CNN architecture is shown in Fig. 1.

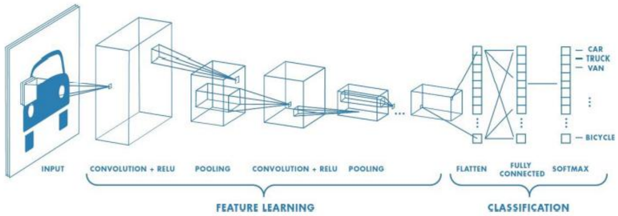
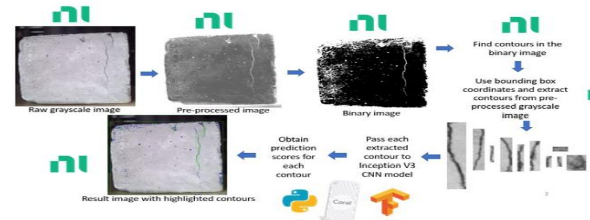


Fig. 1 Architecture of Convolutional Neural Network

Kumar and Ghosh [2], used a Ducal Channel Convolutional Neural Network model for crack detection in concrete. A dataset of 3600 images containing cracks and non-cracks with a dimension of 256×256 pixels was prepared. The primary network used was a single-channel convolutional neural network (SCNN) in which feature extraction was done using intermediate max-pooling layers. The model was trained with a learning rate of 0.0005 and achieved an accuracy of 90.5%. For making the model robust, data augmentation was performed using random rotations, shifts and zooming. This led to a drop in accuracy to 82.25%. For optimizing this model, they introduced a second channel, which had shallow network structure and skip connections, thus making the model to be a Dual-channel Convolutional Neural Network. The new model was trained with 6400 images at a learning rate of 0.0005 and achieved an accuracy of 92.25%. The average time taken by each epoch was 159.031 seconds.

EDGE COMPUTATION

Edge computing is changing the way data is being



handled, processed and then delivered from many devices all over the world. The tremendous growth of internet-connected devices – the IoT – alongside new applications that needs real-time computing power, continues to drive edge-computing systems. Faster networking technologies, like 5G wireless, are allowing edge computing systems to accelerate the creation or support of real-time applications, like video processing and analytics, self-driving cars, AI and robotics. Edge computing simply provides information processing close to the edge that is data gathered through IoT devices are passed through the edge computing devices to act like a gateway where data are interpreted quickly before being pass through the internet to be sent to a server or cloud storage for further processing if necessary or just for data-keeping. To achieve high-speed data transmission, google has launched hardware called Edge TPU (Tensor Processing Unit) that can be connected by just using a USB connection. TPU is an AI accelerator application-specific integrated circuit (ASIC)

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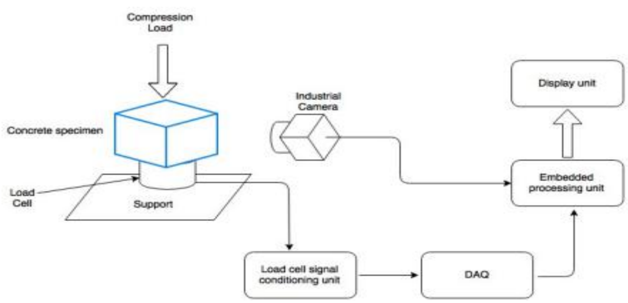
developed specifically for neural network machine learning in the TensorFlow ML library.

Proposed Computer Vision System for Concrete Crack Monitoring

Fig. 2 shows a complete block diagram of proposed computer vision system implemented at Heavy Structures Laboratory of Nirma University for compression testing of concrete cubes. In this system, for crack detection model, the previously re-trained Inception v3 model is used along with a LabVIEW GUI especially developed for crack



detection. It follows the same methodology but with a few changes. The input image is read by the LabVIEW and is

Fig 2. Concept Block Diagram

processed in LabVIEW itself. The input image is first converted into a greyscale image and then to a binary image. Contours are found in the binary image using LabVIEW only. Using the bounding box coordinates of the found contours, different regions of interest are extracted from the greyscale image. All these steps are performed on LabVIEW platform. After extracting the contours, each contour is now passed to the CNN-based re-trained Inception v3 model to classify them as crack or non-crack and to obtain a prediction score for each contour. The final output is again displayed in the LabVIEW GUI with all the contours found and classified as crack or non-crack. The complete flowchart of crack detection using Control panel unit(CPU)+tensor penal unit(TPU) with NI Labview, python and Tensorflow is shown in Fig. 3.

Fig. 3 Flowchart of crack detection performed using a custom CNN model on a CPU + TPU with NI LabVIEW, Python and TensorFlow

The LabVIEW Graphical User Interface (GUI) developed in this system has the facility to select whether the model is to be run on CPU alone or CPU + TPU. Based on the selection, if CPU alone is selected the re-trained inception v3 model with python is used, and if the CPU + TPU option is selected, then the re-trained inception v3 edge TPU compatible model is used for crack detection purposes. The GUI also has an option using the crack detection model in live stream mode in which the images of the concrete block are captured by the camera in real-time and sent to the crack detection model along with the real-time load applied on the concrete block. If live stream mode is not selected then images and load cell data are read from a saved folder on the server device. LabVIEW analyses different characteristics of cracks like the number of cracks and area of cracks and plots a graph of Load vs Number of Cracks, Load vs Crack Length, Load vs Area of Cracks and Load vs Time. Fig. 4 presents screenshot of proposed system showing image information like no. of cracks. Along with crack information, preview of images is given so that the portion of the cube to be focused can be changed.

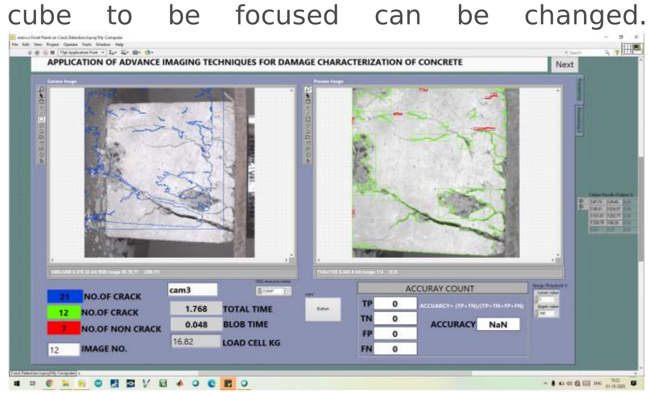


Fig. 4 Concrete Crack Detection Model Result

Various graphs produced in the system for crack analytics like Load v/s Number of cracks, Load v/s Crack length, Load v/s area of crack and Load v/s time are presented in Fig. 5.

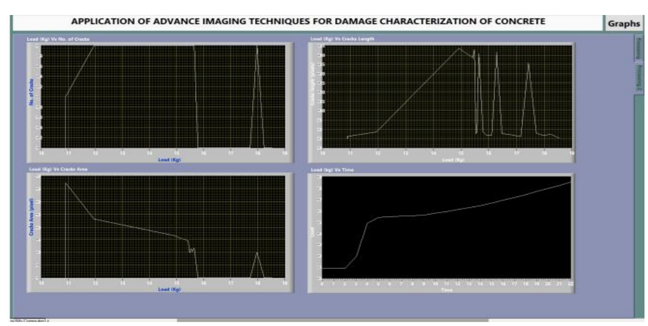


Fig. 5 a) Load vs Number of Cracks, b) Load vs Crack Length, c) Load vs Area of Cracks and d) Load vs Time

Above data obtained from proposed Computer Vision System helps in assessment of structural health of concrete structures.

Concluding Remarks

The computer vision system proposed in this paper perform repetitive and monotonous tasks of concrete structure ealt monitoring at a faster rate and simplifies the work of manual inspection. Several tasks of health monitoring can be automated without the need for human intervention. Computer vision systems that have been trained very well will commit zero mistakes in crack detection and result in faster delivery of high-quality outcomes.

When run with LabVIEW in CPU (central processing unit) + TPU (tensor processing unit) mode, the best accuracy is achieved with a re-trained Inception v3 model, updated to Edge TPU compatible model, with an accuracy of 93.20 percent. A LabVIEW user interface is developed in this system. The input images are first processed by LabVIEW to extract different contours, and then each contour is analyzed by a re-trained Inception v3 model to determine whether they are crack or non-crack. LabView also included a feature called Camera Mode (live-stream crack detection), which uses a camera's live feed to detect cracks in concrete blocks. Load vs. Number of Cracks, Load vs. Length of Cracks, and Load vs. Area of Cracks graphs are also available from this system, which are very useful for health monitoring. Google Coral Edge TPU is used in this system to boost the computational power. Based on the comparison of the computational time required to process an image using a CPU and a CPU + TPU combination, it is observed that the use of TPU greatly reduced the computational time.

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