Convolutional Neural Network Based Improved Crack Detection In Concrete Cubes

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Abstract: Advancement of imaging technology and computing resources make crack detection in concrete automated using a vision-based approach. The present work focuses on crack detection in laboratory-scale concrete cubes used for the characterization of concrete using the convolutional neural network. The major challenge in the said application is to remove inherent noise and dents from the uneven surface of the test cube. A laboratory-scale image acquisition setup was developed to acquire consistent images of concrete cubes. Inceptionv3 architecture was trained to detect the cracks in concrete cube surface images in the most accurate manner. The Inceptionv3 model was trained and validated using more than 80,000 crack and 80,000 non-crack images dataset prepared manually using the concrete cube surface images. Popular data augmentation techniques were used to generate the training dataset. An average of 97.49% accuracy and 7.38% cross-entropy are achieved in the training whereas 97.67% accuracy and 7.69% cross-entropy are achieved in the model validation. The training was carried out with a batch size of 100 and 5,000 epochs. An average accuracy of 99% has been achieved during the performance evaluation of crack detection on concrete cubes as presented in the results. The average values of precision, recall and F – score are obtained as 0.88, 0.98 and 0.93 respectively.

Keywords: Convolutional neural network; Concrete crack detection; Concrete cubes; Deep learning; Structural health monitoring

1. INTRODUCTION

Concrete has been the most necessary element of construction activities ever since it was discovered. It is basically a composite material consisting of cement, aggregates, sand, water and admixtures. Factors such as heavy load, excess water in the cement mixture, corrosion of reinforcement steel and expansion and shrinkage cause cracks in concrete. The behaviour of different types of concrete should be investigated in order to use them in practical applications. Before taking them into an application, it is important to assess their effectiveness by casting and testing them in the laboratory. Various parameters such as compressive strength, flexural strength, the strain developed, displacements and temperature profile are evaluated during the testing of concrete elements in the laboratory. Compression tests and tensile tests are carried out on laboratory concrete elements to understand their behaviour under loading. There is a need to inspect such concrete elements during testing and inspect their surfaces for crack detection which in turn helps obtain important parameters like crack length, width, depth, crack initiation and number of cracks with the application of force online during the experiment. Conventionally, sketches of cracks in a laboratory environment are manually drawn to understand the behaviour of the concrete elements. The process requires good knowledge and experience in concrete testing. Human reach is limited and non-optimal. It also is affected by factors such as cost, time and discrete inspection. The majority of the inspection is carried out with manual observations which have various disadvantages [1] [2][3].

Evidently, automation of the monitoring process must be developed and deployed at critical points in order to ensure continuous inspection of the concrete structure. Computer vision plays a pivotal role in this approach. High-resolution cameras can be deployed in locations which are continuously needed to be observed. However, analysing a perpetual feed of thousands of images is a very difficult task which requires artificial intelligence for the economical examination of images. Cracks are produced by breaking or fracturing. It is a partial separation of concrete into two or more parts. Various types of cracks based on their structure are micro crack, thin crack, sealed crack, mixed crack, line-like crack, minor crack, tiny crack, medium crack, large crack and complex crack[4]. Concrete crack has certain external features such as lower pixel intensity than the background, may be discrete or continuous, has a large area as compared to noises but lower than the background and

their growth is purely random but depends on applied load [5].

Various crack detection techniques for different surfaces like acoustic-based crack detection, ultrasonic pulse velocity etc. have been widely used by practising professionals. Although these methods provide correct measurements, the limitations of these methods are manual observation, human intervention, required expertise requirement, slow, costly and requirement of sophisticated instruments. Image-based crack detection methods have shown lots of promise due to the advances in computing technology and reduced cost of image acquisition devices. Image-based methods provide advantages like good repeatability, reliability, fast response, lower cost and can provide continuous observation of crack detection. With the advances in low-cost computational resources, efficient algorithms and different applications of artificial intelligence in newer domains are being explored by researchers and industries. Machine learning, deep learning and convolutional neural network. are being used more widely than ever before and are deployed in various innovative applications. Applications such as object detection, object classification, recognition, segmentation and clustering are addressed using the power of different types of artificial intelligence-based approaches[6].

Conventional image processing-based methods have been applied by researchers. Researchers have presented a very comprehensive review in the domain of crack detection using computer vision [7][8][9][10][11]. Similar classification work carried out on various concrete structures or elements like the interior as well as exterior walls of the building, sewer pipes, buried pipes, pavements, concrete floor, aircraft structure, heritage sites, historic monuments, reinforced structure, nuclear vessels and structures [12][13][14][15][16][17][18][19][20][21][22].

Image processing-based algorithms used to the improvement of crack detection on different types of concrete elements and structures have been explored by researchers. Work on algorithms to measure crack properties like length, width, and the orientation of cracks developed on concrete surfaces have been carried out [23][24][25]. Largely they have tried to formulate different algorithms and methods to identify cracks on the surfaces of various concrete elements. Uneven concrete surface, random noise on the surface, voids, dents, colour variations and stain marks make it difficult to identify or formulate an algorithm which can accurately locate cracks and further carry out an assessment of the structure under observation.

Out of the numerous methods and algorithms available in the domain, convolutional neural network-based models are used in image processing and computer vision-based applications. Liang et al. presented work comprising of a Convolutional Neural Network (CNN) based prognosis to detect potential faults from customized machining processes[26]. George Sabu et. al. presented work on facial visual cues-based deception detection [27]. An intelligent image classification system was developed to study plankton distribution through the classification of the plankton images taken by underwater imaging devices using convolutional neural network[28]. Similar interesting and innovative studies based on CNN were carried out and presented.

AlexNet[29], LeNet, ImageNet [30], MobileNet[31], Inceptionv3[32], VGG16 [33], ResNet50[34], MatConvNet[35], DenseNet are some of the popular model architectures which are used widely for different vision-based applications. These models, their derivatives and new model architectures are designed for image-based crack detection for various different concrete and other civil structures which are prone to damage. One of the motivations behind the increased use of such convolutional neural network models for crack detection is the variations in the images of the crack. Structures are of different types and these structures have numerous shades, noises, dents, strain marks and discolouration present on the external surface along with cracks. Another major factor is the image-capturing apparatus and methodology deployed. If the acquired images are blurry, poorly illuminated, has non-uniform illumination or saturation, it becomes extremely challenging to detect the cracks accurately. Hence, CNN became a popular choice among researchers while addressing the problem of crack detection. Major work carried out in the domain is discussed here.

Özgenel et. al. proposed work on performance comparison of different pre-trained CNN for crack detection in buildings[36]. AlexNet, VGG16, VGG19, GoogleNet, ResNet50, ResNet101, ResNet152 are pre-trained models compared in the work. These models were trained, tested and validated on different dataset sizes of concrete pavement, concrete building, and brickwork building images. The authors advised training the network with a limited number of images during training covering the variance in the images to avoid overfitting and reduce the training time. A computer vision-based method was proposed by Tung et.al. in which weighted median filter, image opening, Otsu's thresholding, and measurement of morphological features are executed, to automatically detect cracks in concrete structure[37]. The authors achieved an accuracy of 90%.

An automatic pavement crack detection was proposed by Vishal et. al. [38]. The system used YOLO v2 Deep Convolutional Neural Network (DCNN). The road crack images were classified into 8 different classes longitudinal, linear, lateral, alligator cracks and others. Authors have utilized CNN to develop an end-to-end crack detection model for bridges. Atrous convolution, Atrous Spatial Pyramid Pooling (ASPP), and depthwise separable convolution were used in the model and achieved an accuracy of 96.37% [39]. If it is unsafe to observe inaccessible structural members, the use of an automatic vision-based system becomes evident. Unmanned Aerial Vehicle (UAV) based concrete crack

identification was proposed by Kim et.al. [40]. Similarly, UAVs were used for different applications like concrete bridge inspection[41], and for surveying, mapping, and navigation [42]. Shadows and noises in the images captured cannot be fully removed, filtered, or segmented and the CNN-based object detection algorithms may confuse them for cracks.

The success and accuracy of the image processing application depend majorly on three things the image acquisition setup, the algorithm used and coded, and the computing hardware deployed. Crack detection for concrete surfaces can be categorized into two categories. Outdoor and general environment applications where the images acquired are inconsistent. As an example, crack detection on bridge pavement can be considered in the general environment. The second category comprises fixed, indoor environments for example crack detection on nuclear vessels, sewage pipes, and tunnels. The crack detection applications focused on the work is a fixed, indoor environment application. Consistency of acquired images greatly affects the overall accuracy and performance of crack detection or for that matter majority of image processing applications. Considering these factors, the methodology adopted and present in the work consists of an ingeniously developed image acquisition setup, CNN-based crack detection along with data augmentation. The approach was used for accurate crack detection on the laboratory-scale concrete cubes.

2. MATERIALS AND METHODS

Accurate crack detection is an important step in the assessment and maintenance of the concrete structure as well as laboratory concrete testing. Conventionally concrete cracks are inspected manually by an expert via visual observation of the concrete surface, which is intrinsically subjective as it depends on the experience of an expert and the methods are periodic. In a few cases, where it is unsafe to observe inaccessible structural members, the use of an automatic vision-based system becomes evident. The concept of deep learning can be well deployed for image-based applications where the object under observation has immeasurable and uncontrollable variations. The prime objective of the work is to detect cracks in a concrete cube cast in a laboratory. The size of the laboratory-scale concrete cube considered here is 15 cm × 15 cm × 15 cm. In order to obtain consistent, noise-free and uniformly illuminated images an indigenous image acquisition setup was developed. Figure 1 shows the setup which comprises an industrial camera coupled with a lens, white colour lights, an adjustable stand, and mounting for the camera and lights.

An Imaging source DFK72 UAC02 USB 2.0 industrial camera with a 5 MP CMOS sensor used along with an 8 mm Tamron lens M118FM08 was used for image acquisition. Two 24-watt white colour square-shaped LED panel lights were used to provide consistent illumination. Both camera and panel lights were mounted on an adjustable stand so
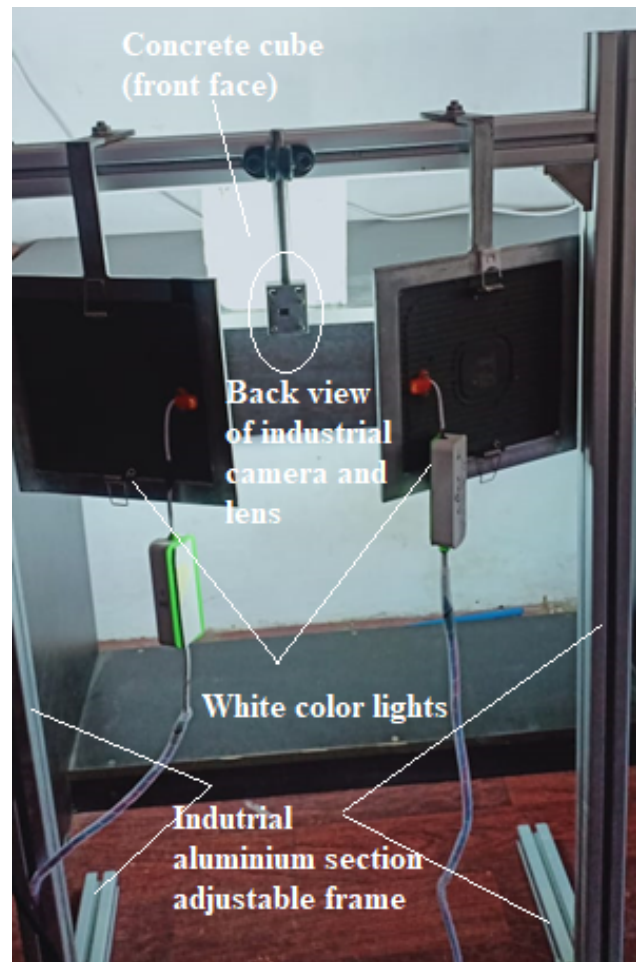

Figure 1. Front view of image acquisition setup with annotations

that their position and orientation can be adjusted as per the need. They were adjusted properly such that the centre of the concrete cube was kept on a table and the centre of the camera-lens are on the same line. The adjustment enabled orthogonal view images of the concrete cube. The panel lights were kept at the same vertical position as the camera and oriented inward so as to throw maximum illumination of the cube. The adjustable stand was fabricated using an industrial aluminium section of square shape and size 40 mm × 40 mm. The design makes the image acquisition setup more versatile and suitable for various other applications with minimal or no change. With the help of the developed image acquisition setup, images are well-illuminated for proper crack detection. The use of white colour illumination will give enhance the contrast of the image while increasing the threshold difference between crack pixels and non-crack pixels.

For image acquisition, IC Capture 2.4 software provided by The Imaging Source Europe GmbH was used. One of the prime requirements of image processing applications is good resolution, uniformly illuminated, and consistent

Figure 2. Concrete cube surface images without illumination and experimental setup

images. Concrete cubes are greyish in nature and have a narrow difference in the intensities of cracks and random dents on the surface of concrete cubes. These dents may be detected as cracks by conventional image processing-based algorithms which consider greyscale intensity for segmentation and detection. The location and size of these dents, small cracks, and large cracks are random in nature. Hence, obtaining uniformly illuminated and consistent images is of prime importance looking into crack detection accuracy. Figure 2 shows the sample images acquired using the industrial camera with the lens but without illumination and experimental setup. These images lack consistency in terms of contrast, the improper orientation of the object, presence of shadow and background. All six images have a lot of background and the greyscale intensity is not consistent as well. In addition to that, the orientation of the concrete cube with respect to the edges is not aligned. The presence of shadow in the upper half of the cube is also evident in these images. These issues are visually evident and make the algorithm development extremely challenging and time-consuming. For an instance, threshold operation applied on these images with a common threshold value will result in variable segmentation. Hence, it is very difficult to accurately segment the crack and non-crack or background with conventional image processing algorithms.

Figure 3 shows the images captured with the acquisition setup using the illumination. The flexibility of the acquisition setup leverages the user to acquire the image of a concrete cube with limited background, improved contrast, and maintain the overall histogram of the image, well oriented. Further, an important advantage of using an industrial camera over a normal webcam or any other camera is that the camera acquisition parameters can be tuned to capture good images. Moreover, industrial cameras are capable to transfer images to the computing device on the fly and at a good frame rate. For an instance,
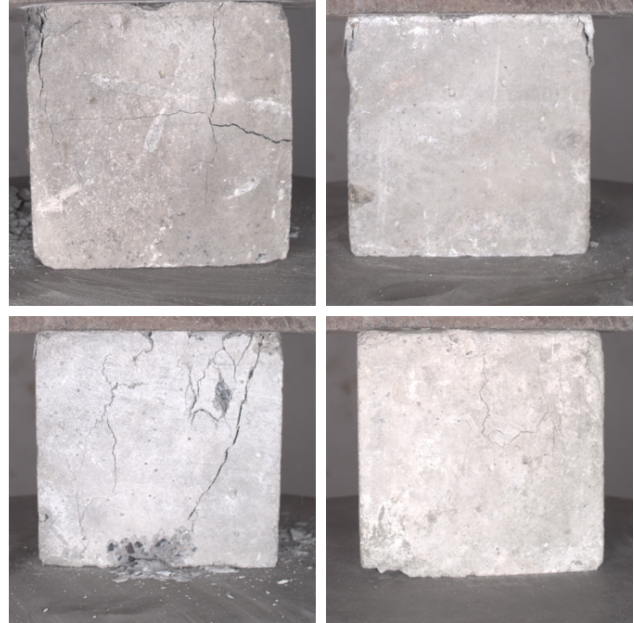

Figure 3. Concrete cube surface images with illumination and experimental setup

an industrial camera has the capability to tune parameters like exposure time, white balance, gamma, saturation, and others. With webcams, these parameters are in auto mode which was unsuitable for such kinds of applications.

On visual comparison of acquired images shown in Figure 2 and Figure 3, it is evident that the images captured with the acquisition setup are consistent and well illumination as compared to the ones captured without setup. Orientation, illumination, background, and greyscale intensity look quite consistent in all the images. No signs of shadow are visible in these images. These well-acquired images immensely assist in the dataset generation for CNN model training and improve the overall performance of the CNN model for accurate crack detection. A conventional image processing technique for crack detection would start to consist of functions like pre-processing, segmentation, and classification. Various researchers have carried out work on image pre-processing techniques to improve the detection process[43][25][44].

Different convolutional neural networks have gained wide popularity which gives rise to novel applications, modified and new architectures. With the tools and frameworks like TensorFlow, Keras, Caffe, Microsoft Cognitive Toolkit/CNTK, PyTorch, MXNet, and Chainer building and deploying CNNs have become fairly simple, fast, computationally affordable, and efficient. Inception version 3 convolutional neural network model was used to classify the concrete cube images for a crack part and a non-crack part. The model consists of two parts, one for feature extraction based on convolution layers and the second one for classification using fully connected layers with a

softmax activation function. Research has also shown the use of transfer learning which allows the reuse of the feature extraction portion and re-train the classification with a custom dataset [45][46]. The model has 42 layers network to obtain a low error rate with fewer parameters. The model was based on the concept of factorization wherein the convolution operations were factorized to reduce the number of connections and parameters without decreasing the model efficiency. The model has been developed as a part of the ImageNet Large Scale Visual Recognition Competition organized in 2015 where it stood as 1st runner-up. Since then it has been used in different image classification applications like flower classification [47][48].

The majority of the applications developed using CNNs have ground truth images or known labels or classes for supervised learning. MNIST dataset which is very popular for handwritten digit recognition, CIFAR-10, MS COCO, and many others. An application of handwritten digit recognition has a large dataset of all digits covering up the maximum possible variations that can occur in the handwritten digits. These digit images are used for training, testing, and validation of the CNNs. For concrete crack detection, ground truth images are not so commonly available. Also, the images for laboratory-scale concrete cubes are not available. Moreover, concrete cracks are of various sizes and shapes and have good intensity variations as well. Feature-based classification seems a trivial option as the features in the concrete crack images is not explicitly distinguishable from that of non-crack parts. Due to this, CNN's are preferred as compared to other feature-based classification methods.

CrackNet is a convolutional neural network model applied for crack detection on road surface images [49]. Another CNN called CrackNet-V has been deployed for pixel-level crack detection on 3D asphalt pavement images [50]. To the best of our knowledge, CrackNet is not used for crack detection on the concrete surface. In addition to that, no particular CNN model has been widely researched.

In the present work, the development of the CNN application starts with data set preparation. With increasing applications of structural health monitoring in a variety of areas, CNN models like CrackNet will be developed solely for concrete crack detection. Even the dataset of concrete cube crack images is not openly available as of date. Researchers who have addressed the crack detection application have created or generated their own dataset with manual labeling [51]. Few other data sets of crack and defect detection were found and discussed here.

Structural Defects NETwork (SDNET) 2018 is available on Kaggle (Structural Defects Network (SDNET) 2018) Sattar Doragshan et. al. presented this SDNET 2018 dataset in their work [52]. The dataset was created for training, validation, and benchmarking of artificial intelligence-based crack detection algorithms for concrete. It contains 56,000 images of cracked and non-cracked concrete bridge decks, walls, and pavements. A total of 230 images of cracked and non-cracked concrete surfaces are captured using a 16 MP Nikon digital camera. Each image is segmented into 256×256 pixels sub-images of crack and non-crack parts. Each sub-image is manually labeled as 'Cracked' and 'Non-cracked' depending on the presence or absence of a crack in the image. The dataset also includes images with a variety of obstructions, including shadows, surface roughness, scaling, edges, holes, and background debris. SDNET2018 can be useful for the continued development of concrete crack detection algorithms based on deep learning convolutional neural networks, which are a subject of continued research in the field of structural health monitoring. COncrete DEfect BRidge IMage (CODEBRIM) dataset was prepared and worked upon by Martin Mundt et. al. [53]. The dataset comprises five common defect categories which are crack, spallation, exposed reinforcement bar, efflorescence (calcium leaching), and corrosion (stains), found in 30 unique bridges.

A dataset containing pavement surface cracks with pixel-wise annotation was proposed and used in the work presented by Qipei Mei et. al. [54]. Another similar asphalt pavement labeled dataset was worked upon by Zhun Fan et. al. in their work on pavement crack detection using encoder-decoder architecture [55]. Eberechi Ichi et. al. developed a Non-Destructive Evaluation (NDE) dataset named Structural Defect NETwork 2021 (SDNET 2021) [56]. The dataset consists of three NDE methods namely Infrared Thermography (IRT), Impact Echo (IE), and Ground Penetrating Radar (GPR) data collected from five in-service reinforced concrete bridge cracks. The prime objective of the dataset was to carry out concrete delamination detection and reinforcement corrosion detection.

As observed in the dataset presented in the literature, the availability of crack-related datasets started in 2018 onwards. None of the previous datasets was prepared for standard concrete cubes used in laboratory testing. Due to the unavailability of the labeled dataset and ground truth images for laboratory-scale concrete cubes, the solution of the application becomes more challenging and time-consuming.

Normally crack detection using CNN is performed with two approaches. One is patch or contour-based and the other one is pixel based. In the contour-based approach, contours obtained after the segmentation operation are segregated into crack and no-crack classes manually. Each patch image either contains a crack or a non-crack. Both types of patches have some background surface of the cube. The second type of approach is pixel-based, each pixel in the image is annotated for cracks. Using an annotation tool or labeler tool, individual pixels are labelled into classes like cracks, non-cracks, and background depending on the objective and requirement of the application. Dataset generation and labeling or ground truths were generated manually which
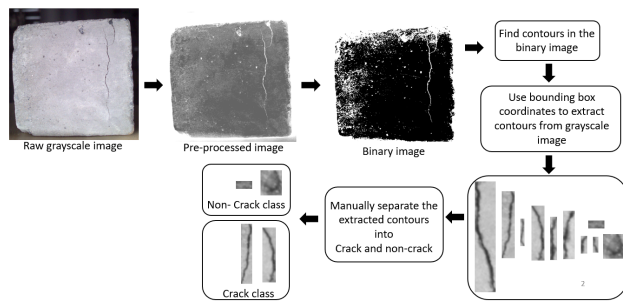
Figure 4. Dataset generation flowchart

Figure 5. Sample images of non-crack greyscale contours

Figure 6. Sample images of crack greyscale contours

was a time-consuming and tedious task. The contour-based approach was used in the present work. Initially, the binary contour dataset is prepared, trained, and evaluated for performance. Two classes are considered here crack class and non-crack class.

Concrete crack images were captured with the custom-developed image acquisition setup. In order to prepare the training and testing dataset, the acquired images were first prepossessed and binarized using the local threshold method. The surface dents, noise, and shadow present on the concrete cube surface were removed by pre-processing[44]. The binarized images consisted of crack contours and non-crack contours. A binary image would contain roughly between 0-20 crack contours and 100-250 non-crack contours. The number of cracks and non-crack contours largely depends on the pre-processing and threshold operation along with the cracks and non-cracks present on the surface of the concrete cube. Considering this fact, an optimum value of threshold was used such that all crack contours are properly segmented.

Figure 3 shows the entire process of dataset generation. The raw greyscale image collected during the compression test is pre-processed and binarized. Coordinates of the contours bounding box are identified and used to extract the contours from greyscale images. There is no change in the size of the image and its resolution during pre-processing or binarization. Hence, the coordinates identified from the binary images can be used to extract the contours from the greyscale image as there is no change in the spatial coordinates. These greyscale contour images are saved and manually labeled as cracks and non-cracks. Around 200 different images of various concrete cubes were acquired using the developed image acquisition setup and passed through the process of dataset generation. The extracted contours of each image were manually separated into the crack and non-crack classes with utmost care.

Figure 5 shows a few of the extracted non-crack contours whereas Figure 6 shows the extracted crack contours. Greyscale images contain much more information as compared to binary images. Binary contour images of cracks and non-cracks contain limited information related to the
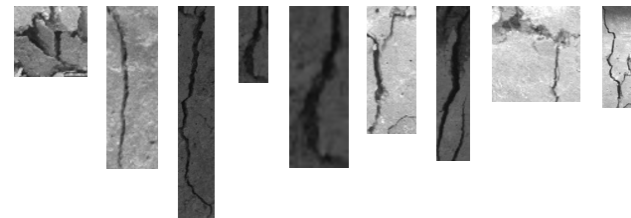
shape of the contour. The information contained in the binary images may not be distinguishable in certain cases when the size and shape of crack contours match that of the non-crack contours. In order to overcome the issues, greyscale contour images of crack and non-crack are used for the model training. The intensity variations in the non-crack contour images are evident from the samples shown in Figure 5. Few contour images are dark whereas others a bright, even though standard illumination and industrial-grade vision hardware are used to acquire the images. This was due to the inherent variations in the grey nature of the different concrete cubes. Also, a few samples show the dents present on the cube surface and the edges of the cube which are segmented in the binarization operation. Similar to non-crack contours, bright and dark crack contours are seen in the samples. Few contour images have single cracks whereas other images contain multiple or branched cracks. Out of which, the majority of cracks are thin in width and vertical in nature. Spalling of concrete also occurs during the compression test cycle and few crack contours showcase that.

A total of 3,468 greyscale crack contour images and 18,296 numbers of greyscale non-crack contour images were collected. These contour images were manually separated into the crack and non-crack classes with utmost care and saved in the memory. The prepared dataset was used for the training, validation, and testing of the inception v3 CNN model. Train, validation, and test split were considered as 80 - 15 - 15 % of the total dataset respectively. Looking into the number of cracks and non-crack contours images extracted, an imbalance in the class-wise dataset is apparent. As non-crack contours are always higher in numbers as compared to crack contours.

During the compression test cycle, initially, when the applied load is lower, there are no cracks on the surface of the concrete cube. Even after cracks start appearing on the surface with the increase in the compressive load, the number of non-crack contours is much higher than the number of crack contours segmented in the process. In order
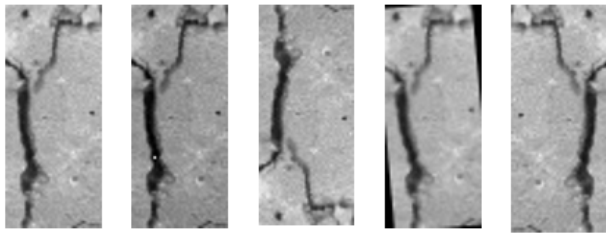
Figure 7. Samples images from the augmented dataset

Figure 8. Flowchart of CNN model training using greyscale image dataset

Figure 9. Flowchart of CNN model testing on greyscale image dataset

to mitigate the issue of data imbalance, data augmentation techniques are used. The imbalance in the number of crack and non-crack contours gets reflected in the CNN model performance as well. Additionally, looking into the demand to provide sufficient variations in the dataset, the extracted crack and non-crack contour images are augmented using flip, rotation, and brightness adjustments operations. In order to solve the issues, data augmentation techniques like vertical flip, horizontal flip, rotation, and brightness adjustments are applied on both crack and non-crack contours to enhance the dataset. In rotation, 5-degree counterclockwise rotation is performed on the contour images while in brightness adjustment, images are first converted into HSV (H – Hue, S- Saturation, V-Value) colour space and intensity values 10 and 25 were added to the value. These augmentation techniques are applied to all the images of crack contours and only selected images of non-crack contours in order to balance the total dataset.

Overall contour images per class are approximately 80,000 after the data augmentation. Exactly 79,445 greyscale contour images of cracks and 80,721 numbers of non-crack contour images are prepared for training. Figure 7 shows a few samples of data-augmented images of a crack contour. In figure 7, the first subfigure is the sample crack contour image, the second subfigure shows the brightness-adjusted image, the third subfigure shows the horizontal flip image, the fourth subfigure shows the rotated image and the last subfigure shows the vertical flip image.

Figure 8 depicts the flowchart of the data set generated from the acquired images and model training. Raw greyscale images acquired with the image acquisition setup were pre-processed initially and converted into a binary image using a thresholding operation. Multiple contours were extracted from the greyscale image by using the bounding box coordinates of contours found in the binary image. The prepared dataset was used for the training, validation, and testing of the inception v3 model.

The flowchart of the complete crack detection process is shown in Figure 9. The figures show the combined approach of the contour extraction process, classification, and visualization. The raw greyscale images are processed to extract crack and non-crack contour sub-images. These images are transferred to the re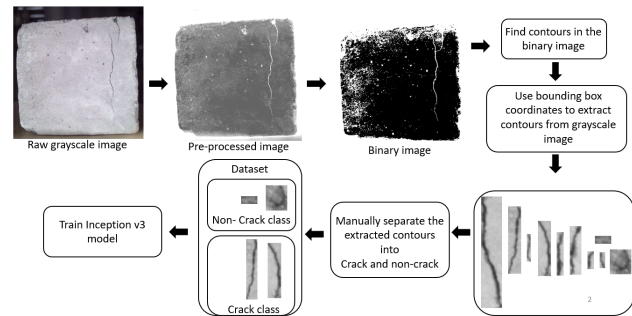-trained inception v3 model for the prediction of crack and non-crack class. The predictions are overlayed on the raw greyscale image using the bounding box. Predicted crack contours are shown with a green colour bounding box whereas non-crack contours are shown with a blue colour bounding box. Results in form of parametric assessment, observations, and crack detection result images are discussed in the next section.
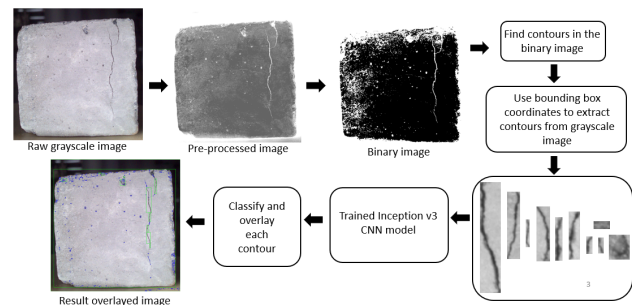
3. RESULTS AND DISCUSSION

All the trained CNN models are evaluated for performance using the unseen data in order to judge their practical applicability and whether it requires modification or not [57]. The evaluation of inception v3 CNN model which is used in the current was evaluated for performance. The generated dataset was divided into a train, validate and test split. 80% of the data was used for training, 10% of the data was used for validation and the remaining 10% of the data was used for model testing. The testing was carried out to evaluate the accuracy of the model after the training was completed. To achieve an optimum CNN model performance, all the possible variations in both crack and non-crack classes were used for the training. For validation, contours images that were not used for training or testing were used. For training, validation, and testing of the inception v3 model, a python code was developed.

Tensorflow, Numpy, and various other libraries were imported for the training of the model. The trained model was saved as .pb file and the labels were stored in a text

file. The.pb format is the protocol buffer format used in Tensorflow to hold models. The format is a general way to store data by Google because it is much nicer to transport, as it compacts the data more efficiently and enforces a structure to the data. The number of epochs was kept at 5,000 while the initial learning rate was kept at 0.01. The batch size was kept at 100 and the number of batches was 1,600 for the training. During the training process, the validation was carried out using the entire validation set to achieve more stable results across the training iterations. Once the training was completed after the specified number of epochs, the final accuracy testing of the model was carried out using the entire training set. This testing set was used only once after the training is completed.

The model has a greater number of layers in the output layer because inception v3 was used for the classification of the image from the ImageNet database. The present application was focused on the binary classification of crack and non-crack contours. And hence, the model architecture is modified in order to meet the requirements. The final dense layer in the model was updated with two neurons in order to classify cracks and non-cracks. The softmax function was used as the activation function in the output layer and cross-entropy is used as the loss function to train the model. The gradient descent optimizer available in Tensorflow was used for the optimization of mean cross entropy which was the loss function used. Other essential hyperparameters and model requirements are defined as per the standard or kept unchanged. Figure 10 shows the graph of the epochs versus accuracy and cross-entropy of training and validation of the model.

An average of 97.49% accuracy and 7.38% cross-entropy are achieved in the training whereas 97.67% accuracy and 7.69% cross-entropy are achieved in the model validation. The training and validation performance of the inception v3 model trained with a balanced and augmented greyscale contour image dataset is presented. And the best model performance is shown in Figure 10. Various other instances of model training, evaluation, and interpretation were carried out before this. The initial training instances were carried out on the Google Colab platform. However, later on, a personal computer is used to meet the overall computing demands of the system. The computer has an intel core i7 – 9750H Central Processing Unit (CPU) with a clock frequency of 2.60 Giga Herts (GHz), 6 cores, 12 logical processors, 16 Giga Byte (GB) physical Random Access Memory (RAM), 256 GB Solid State Drive (SSD), 1 Tera Byte (TB) Hard Disk Drive (HDD) and Windows 10 home version. An additional 4 GB NVIDIA Geforce GTX 1650 graphics card is available. The training was carried out with 5,000 steps and a batch size of 100 was used. The model is trained properly and no signs of underfitting or overfitting are observed shown, which is evident from the graphs shown in Figure 10. Results in form of parametric assessment, observations, and crack detection result images are discussed in the paper.
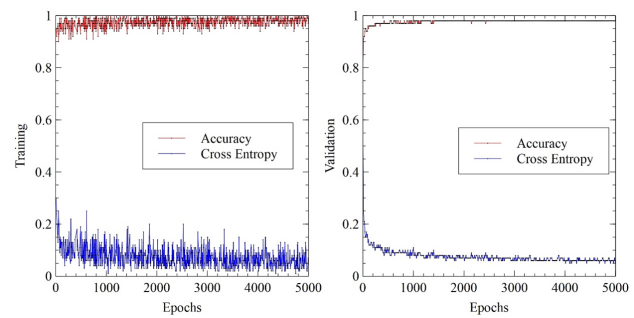

Figure 10. Training and validation performance of inception v3

Table 1 shows the performance evaluation of the inception v3 CNN model trained using a balanced greyscale contour image dataset. The problem of data imbalance is addressed using data augmentation. After the augmentation process, around 80,000 images per class are used for the training of the inception v3 model. The performance analysis is carried out on 15 full images of different concrete cubes acquired using the experimental setup. These images are chosen to consider different instances during the compression tests of concrete cubes. Due to this, the number of crack and non-crack contours present in each of these images is different. The minimum and the maximum number of crack contours found in these test images are 4 and 13 respectively. On the other hand, the minimum and the maximum number of non-crack contours found are 146 and 355 respectively. Out of the 8.27 average number of crack contours, 6.80 crack contours are correctly classified as crack whereas 1.27 crack contours are incorrectly classified as non-cracks. On the other hand, 220.67 non-crack contours are correctly classified as non-cracks and the remaining 1.20 non-crack contours are erroneously classified as cracks. The average values of accuracy, recall, precision, and F-score are 0.98,0.88,0.99, and 0.93 respectively. The obtained performance meets the expectation.

The results obtained with the current methodology are compared and analyzed with other methodologies from the literature. The comparison is performed with the literature methods wherein convolutional neural networks are used. Table 2 shows the comparison of different methods proposed by authors based on the model's testing accuracy along with other factors such as crack surface, CNN model used, image acquisition setup, and dataset used in the work. The majority of the work has been carried out on pavement images of different locations, buildings wall images, and concrete bridge images. Based on the CNN model average accuracy, it is evident from the comparison that the proposed method obtained the best results. Other models like MatConvNet, ConvNet, modified AlexNet, VGG-16, and a few other customized CNNs obtained good results (Shengyuan Li) (N. A. M. Yusof) (Zhang Lei) (Gopalakrishnan) (Pauly) (Hongyan Xu). Some of the authors have used smartphones and DLSRs for image acquisition of cracks at

different locations. For pavements, authors have focused on the use of off-the-shelf 3D vision systems. None of the authors has included the synchronization of cracks with the applied load which is performed in the present work. Since 2015, the use of convolutional neural networks and other related methods has been observed in the literature. From the numerical analysis reported in Table 1 and the performance comparison of different methods mentioned in Table 2, the proposed method shows overall improved performance for concrete crack detection in laboratory concrete cubes.

Table 2 shows the comparison of different methods proposed by authors on the basis of the model's testing accuracy along with other factors such as crack surface, CNN model used, image acquisition setup, or dataset used in the work. The majority of the work has been carried out on pavement images of different locations. On the basis of the CNN model average accuracy, it is evident from the comparison that the proposed method obtained the best results. Other models like MatConvNet, ConvNet, modified AlexNet and a few other customized CNNs obtained good results[58][59][60]. The proposed model performed considerably well when evaluated for precision, recall, and F-1 score with that of other presented models. For instance, P-0.84, R-0.90, and F-score of 0.87 was obtained by Yue Fei et. al. [50], Allen Zhang et al. [49] reported P-0.90, R- 0.89, F-score- 0.89 while the proposed method obtained P-0.98, R-0.88, F-score- 0.93. From the numerical analysis reported in table 1, results shown in figure 8, and performance comparison of different methods mentioned in table 2, the proposed method shows overall improved performance for concrete crack detection in laboratory concrete cubes.

4. Conclusions and Future Work

Concrete crack detection is a trivial problem owing to the inherent variations on the surface, fluctuating light, and image acquisition conditions. The proposed methodology utilized the concept of transfer learning in a convolutional neural network for crack detection in images of laboratory-scale concrete cubes. Inceptionv3 CNN model has been used here, trained, tested, and validated on concrete cube images captured by the custom-developed image acquisition setup. The setup allowed an improved image acquisition process in terms of consistency, uniform illumination, and better contrast. A novel approach was proposed which uses the contours extraction method to generate the crack and non-crack contour image dataset. Data augmentation methods like vertical and horizontal flip, rotation, and brightness adjustments were used to correct the dataset imbalance and generate 80,000 contours images per class which were manually separated into the crack class and non-crack class. The model was trained with 80% of the dataset and an accuracy of 97.49% was reported. The remaining 10% of the contour images per class were used for the model validation wherein an accuracy of 97.67% was achieved. Testing of the model was carried out on the last remaining 10% of the contours images per class which were not

used for training and validation. An average accuracy of 99% was obtained with detailed analysis, which included precision, recall, accuracy, and F-score. The performance evaluation depicted results, and comparison with previously reported work proved that the proposed methodology has achieved better overall performance and has improved the crack detection process. A similar methodology can be adapted for other laboratory-scale concrete elements like beams, columns, T-junctions, and cubes of different sizes. and other structures of importance. Further, for practical and real-time implantation various off-the-shelf embedded computing platforms and/or USB accelerators can be utilized along with a good processing system.

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TABLE I. Performance evaluation of CNN tested on a balanced greyscale dataset

Image	C	NC	TP	FP	TN	FN	R	P	A	F
1	7	197	5	2	194	3	0.71	0.63	0.98	0.67
2	13	355	11	2	352	3	1.00	0.81	0.99	0.90
3	10	258	10	0	256	2	1.00	0.83	0.99	0.91
4	10	250	9	1	248	2	1.00	0.83	0.99	0.91
5	10	255	9	1	253	2	1.00	0.83	0.99	0.91
6	4	193	4	0	193	0	1.00	1.00	1.00	1.00
7	7	227	6	1	227	0	1.00	1.00	1.00	1.00
8	6	191	5	1	191	0	1.00	1.00	0.99	1.00
9	7	232	6	1	232	0	1.00	1.00	1.00	1.00
10	6	267	5	1	227	0	1.00	1.00	1.00	1.00
11	6	253	4	2	252	1	1.00	0.86	0.99	0.92
12	9	169	8	1	166	3	1.00	0.75	0.98	0.86
13	11	146	7	4	146	0	1.00	1.00	0.97	1.00
14	9	164	6	3	163	1	1.00	0.90	0.98	0.95
15	9	171	7	2	170	1	1.00	0.90	0.98	0.95
Average	8.27	221.87	6.80	1.47	220.67	1.20	0.98	0.88	0.99	0.93

TABLE II. Performance comparison of different methods from the literature

Author	Year	Surface	CNN model	A	P	R	F	Image data
Zhang et al	2016	Pavements	ConvNet	NA	0.87	0.93	0.90	Smartphone
Cha et al	2017	Buildings	MatConvNet	0.98	NA	NA	NA	NIKON camera
Gopalakrishnan et al	2017	Pavements	VGG16	0.90	0.90	0.90	0.90	FWHA LTPP
Pauly et al	2017	Pavements	Custom	0.90	0.92	0.88	NA	Smartphone
Baoxian et al	2018	Pavements	CrackNetII	NA	0.90	0.89	0.90	PaveVision 3D
Xu et al	2019	Bridge	Custom	0.96	0.78	0.88	NA	Phantom 4 Pro
Shengyuan et al	2019	Bridge	Modified AlexNet	0.99	NA	NA	NA	Smartphone
Yusof et al	2019	Pavements	Custom	0.99	0.99	0.98	NA	NIKON camera
Proposed method	–	Concrete cube	Inception v3	0.99	0.88	0.98	0.93	Industrial camera

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