Developing a new deep learning CNN model to detect and classify highway cracks

Abstract

Purpose: Testing the capabilities/accuracies of four deep learning pre-trained CNN models to detect and classify types of highway cracks, as well as, developing a new CNN model to maximise the accuracy at different learning rates.

Design/methodology/approach: a sample of 4,663 images of highway cracks were collected and classified to three categorises of cracks, namely, vertical cracks' 'horizontal and vertical cracks' and 'diagonal cracks', subsequently, using 'Matlab' to classify the sample to training (70%) and testing (30%) to apply the four deep learning CNN models and compute their accuracies. After that, developing a new deep learning CNN model to maximise the accuracy of detecting and classifying highways cracks and testing the accuracy using three optimisation algorithms at different learning rates.

Findings: the accuracies result of the four deep learning pre-trained models are above the averages between top-1 and top-5 and the accuracy of classifying and detecting the samples exceeded the top-5 accuracy for the pre-trained AlexNet model around 3% and by 0.2% for the GoogleNet model. The accurate model here is the GoogleNet model as the accuracy is 89.08% and it is higher than AlexNet by 1.26%. While the computed accuracy for the new created deep learning CNN model exceeded all pre-trained models by achieving 97.62% at learning rate 0.001 using Adam's optimisation algorithm.

Practical Implications: The created a deep learning CNN model will enable users (e.g., highways agencies) to scan a long highway and detect types of cracks accurately in a very short time compared to traditional approaches.

Originality/value: A new deep learning CNN-based highway cracks detection was developed based on testing four pre-trained CNN models and analyse the capabilities of each model to maximise the accuracy of crack detection based on the proposed CNN.

Keywords:

Deep learning, Highway cracks, Classify, Convolutional neural network (CNN), Optimisation algorithms

1. Introduction

Deep learning, as an extension of and supplement to machine learning, has become a new research front in the field of crack detection due to its superior performance in object detection and semantic segmentation (Reichstein et al., 2019). Generally, deep learning-based crack detection methods can be categorized into two main groups, namely region based and pixel-based methods. In recent years, new deep learning models have been introduced to structural crack detection. For example, Lorenzoni et al. (2020) relied on the Seq-Net to realize end-to-end semantic segmentation of crack images. Zhang et al. (2020c) increased the model detection accuracy by integrating the tubelets with deep CNN (T-DCNN) and multi-method detection into a unified loop detection process. Huyan et al. (2020) employed a convolutional neural network (CNN) to realize the pixel level detection. Through the encoder and decoder process, the output was guaranteed to be the same size as input. Thus, the prediction was included in the output probability map. Kang et al. (2020) designed a deep neural network called CrackNet-V to automated pixel-level crack detection on 3D asphalt pavement images.

There have been some studies that applied deep learning algorithms on images collected from cameras in moving vehicles for road crack detection. Mei and Gül (2020b) utilized smartphone in a vehicle to collect road images in Japan and applied a deep neural network on it for road defect detection. This study focused on multiple defect types, bounding boxes were drawn around the defects, but no detailed information could be provided regarding the exact location, shape or orientation of the cracks. Park et al. (2019) proposed a pixel-level detection method for identifying road cracks in black-box images using a deep convolutional encoder–decoder network. The encoder consists of convolutional layers of the residual network for extracting crack features, and the decoder consists of deconvolutional layers for localizing the cracks in an input image. The proposed network was trained on 427 out of 527 images extracted from black-box videos and tested on the remaining 100 images. Mei and Gül (2020a) installed a sport camera on the rear of a vehicle to mimic the behavior of a backup camera. Then they developed an algorithm with a conditional Wasserstein generative adversarial network (cWGAN) and connectivity maps to improve the accuracy of crack detection.

A review of literature reveals that there has been intensive research over the last few years to utilise deep learning and CNN to detect cracks for highways and tunnels. Therefore, there is a need to measure the capabilities of different CNN models to maximise the accuracy of detecting various types of cracks.

With all the above in mind, this research explores the validity and accuracies of four pre-trained deep learning CNN model and analyses parameters of the most accurate CNN models in order to develop a new CNN-based approach to maximise the accuracy of deep learning to detect and classify highway cracks, particularly, horizontal, horizontal-vertical and diagonal cracks. The findings of this study proves that the computed accuracy of the four deep learning pre-trained models were above the averages, as well as the pre-trained AlexNet model was above the top-5 accuracy by 3% and by 0.2% for the GoogleNet model. The most accurate model is the GoogleNet model by 89.08%. Regarding the proposed CNN-based highways cracks accuracy, it is exceeded all pre-trained models based on Adam's optimisation algorithm by 97.62% at learning rate 0.001.

2. Deep learning-based crack detection

In recent years, Machine Learning (ML) based methods are continually being adopted across many aspects during the whole life cycle (Zhong et al., 2016). Deep Learning is recognised as one of the methods that are continually applied especially for complex situations that require extensive amount of data (Mohammadi et al., 2018). With the deserved significance gained by deep learning within the construction industry, many studies began to provide insightful focuses into its forms and applications. A study by Akinosho et al. (2020) has summarised different architectures of deep learning and their applications, which looked at seven (Deep Neural Network, Convolutional Neural Network, Recurrent Neural Network, Auto-encoder, Restricted Boltzmann Machine, Deep Belief Network and Generative Adversarial Networks) conventional architectures.

Roads and Infrastructure can be seen as one of my complex areas that require continual investigations to identify suitable and appropriate remedies to maintain their quality and performance on the long-term (Majidifard et al., 2019). Asphalt-related issues can tangibly be recognised as a major element that requires continual monitoring to assess its performance and potential issues. In fact, and in recent years, many technologies including ground penetrating radar, ultrasonic testing and new sensors have all been used in the detection of asphalt damages (Li et al., 2021) especially those that often occur such as cracking. With the evolution of computer-based techniques, the application of deep learning in detecting issues such as cracking where many studies were conducted to demonstrate crack detection using deep learning. Table 1 shows the previous relevant research to use deep learning to detect cracks. In addition to highlight the findings of each research, the limitation of each study was also stated in order to avoid these limitations in the proposed method in this research.

Table 1. Previous and relevant research

Author	Aim	Methodology	Findings	Limitation
(Chow et al., 2020)	Replace the current laborious inspection programme of concrete defects of civil infrastructure	Deep learning image-based inspection of concrete defects of civil infrastructure	The method is greatly successful in detecting and classifying defects subjected to various environmental conditions such as lighting and capturing angles.	The overall accuracy needs improvement using more sophisticated deep learning models and training strategies
(Liu et al., 2020)	Develop a method to recognise rebars on the GPR data for a deck	Integration of conventional image processing techniques and deep CNN	An overall accuracy of detection of 99.60% ± 0.85%	Larger database size is needed
(Kim et al., 2020)	Develop a methodology for automated bridge component recognition in 3D point cloud data	Using deep learning in conjunction with subspace partition to classify 3D points in each subspace	The developed methodology distinguished bridge components from 3D points bridges to deck, pier, and background, even with curved bridges and bridges with different pier heights.	No able to evaluate surface damages on the point cloud
(Song et al., 2020)	Develop an algorithm to detect and localise rebars in the data from GPR	Integration of conventional image processing techniques and deep CNN	An overall accuracy of detection of 99.60% ± 0.85%	Larger database size is needed
(Qiu, 2020)	Provide a state-of-the-art review of imaging techniques applied for defect detection of fiber reinforced polymer (FRP)-bonded civil engineering structures	Literature review	Recommends the integration of AI approaches with non-destructive testing (e.g., synthetic aperture radar, infrared thermography, laser shearography, and laser reflection technique) to enable the automated defect detection in FRP-bonded civil infrastructures.	Further research is required to combine imaging techniques with artificial intelligence approaches.

(Kohiyama et al., 2020)	Develop a method to detect the input data of an unlearned damage pattern	The collective decision of support vector machines were developed using feature vectors of training data that are stored in the output layer of a deep neural network	The method is capable of detecting data of unrelated pattern	Acknowledging different characteristics such as pulse-like ground motions to further validate the method developed
(Zhang et al., 2020d)	Develop a framework for structural condition identification case, that is, steel frame bolted connection damage.	Application of deep CNN	The developed algorithm, SHMnet, has 100% accuracy using at least four independent training datasets	The performance of the algorithm heavily depends on the quantity and quality of training data.
(Gonzalez et al., 2020)	Automatically detect building materials and types of later-load resisting systems (i.e. building's structural typology)	Using CNN in the dataset of nearly 10000 manually annotated photos at the street level	The developed algorithm has the recall accuracy of 95% on the material type and 60% on three of the eight building typologies.	Prediction of building typologies may not be accurate and should be used in conjunction with census data and expert judgement
(Dorafshan and Azari, 2020)	Investigate the feasibility of using deep learning models (DLM) to detect subsurface defects and overlay debonding from impact echo (IE) data	Application of one dimensional and two dimensional convolutional neural network (CNN) to classify the IE waveforms	The developed method has the accuracies between 45% and 81% (more accurate on the cement overlay than on the asphalt overlay). Also, it was found that the proposed 1D CNN has higher accuracy.	Larger database size is needed

(Zhang et al., 2020b)	Detect and localize moisture damage in asphalt pavements from Ground Penetrating Radar (GPR) B-scan images	Integration of mixed deep CNN including ResNet50 network as feature extractor, and YOLO v2 network, as object detector, with a proposed incremental random sampling (IRS) approach to automatically convert raw GPR images to suitable plot scale GPR images	The proposed detection CNN model shows F1 score (91.97%), Recall (94.53%) and Precision (91.00%), showing that deep learning is reliable in detecting and localising moisture damages in asphalt pavements	Further work is required to try latest deep framework to improve Precision and Recall
(Ghosh Mondal et al., 2020)	Assess multiple damage categories in reinforced concrete buildings due to an earthquake from visual data captured by the sensors mounted on the robots.	Using deep learning-based approaches to detect and classify damages (i.e. surface crack, spalling, spalling with exposed rebars, and severely buckled rebars)	Inception-ResNet-v2 was found to perform better (producing a MAP value of 60.8%) compared to Inception v2, ResNet-50 and ResNet-101. Also, it was found that the processing speed reduces with increase in accuracy.	The practical implementation of the algorithm by integrating it with UAVs or inspection robots is missing.
(Asadi et al., 2020)	Develop a computer-vision method for detecting rebars from concrete bridge deck GPR images	Application of a fined-tuned Histogram of Oriented Gradients/ Multi-Layer Perceptron based binary image classifier which is trained on URIGPR dataset and then applying a post-processing algorithm for removing false detections	The performance of the method is 54.35% more accurate than the result received from GSSI RADAN, which is GPR software, in deteriorated bridge decks	Larger database size is needed

(Lee et al., 2020)	Use deep learning for detecting cracks and measuring the maximum crack width in images from railway infrastructure	Application of semantic segmentation within framework of the deep CNN	Precise labelling of slender objects is important for improving prediction accuracy	Integration of the crack detection with deterioration prediction of track geometry
(Zhang et al., 2020a)	Propose a vision-based single-stage detection algorithm for detecting damages on concrete bridges, unlike most deep learning-based techniques that are built on two-stage, proposal-driven detectors	Application of a real-time objection detection technique, You Only Look One (YOLOv3),	The developed algorithm is able to detect concrete crack, pop-out, spalling, and exposed rebar, and it has a detection accuracy of up to 80% and 47% at the Intersection-over-Union (IoU) metrics of 0.5 and 0.75. It performs better than original YOLOv3 and the two-stage detector Faster Region-based Convolutional Neural Network (Faster R-CNN) with ResNet-101, especially for the IoU metric of 0.75.	The dataset contains many small damages and a complex background information, which could inhibit the algorithms' generalization and capacity.
(Guo et al., 2020)	Identify the damage features from noisy and incomplete mode shapes without the need of using any hand-engineered feature or prior knowledge	Using A deep-learning model based on CNN and design a new network algorithm, a multi-scale module, which helps in extracting features at various scales	The proposed algorithm improves the accuracy of at least 10% compared to other network algorithms	The results are based on the laboratory experiments and the research lacks dataset from actual structures
(Dong et al., 2020)	Develop a non-contact structural displacement measurement method with less user involvement	Using deep learning-based optical flow and validating it through a series of laboratory experiments and a field application	The proposed method, FlorwNet2, has a higher accuracy compared to the traditional optical flow algorithms and decreases the need for human involvements	limited to process uniformed sampled image data

(Dong and Catbas, 2020)	Provide an understanding of the concepts, state of the art approaches and real-world practice of computer vision-based structural health monitoring	Review of the literature	Applications of computer vision-based structural health monitoring are divided into local level and global level. At local level, they are mainly focused on identifying defects such as crack, spalling and delamination. At the global level, they are mainly focused at applications such as displacement measurement, structural behaviour analysis, and vibration serviceability.	This review mainly puts emphasis on two-dimensional computer vision–structural health monitoring applications.
(Sajedi and Liang, 2021)	Develop a framework that quantifies the confidence level of computer vision and deep learning models on vision-based structural health monitoring	Using Bayesian neural network for deep vision of structural health monitoring models	Bayesian inference is proposed to provide an uncertainty output for the corresponding predictions in the inspection processes.	Larger database size is needed
(Bae et al., 2020)	To enhance the crack detectability by augmenting the pixel resolution of the raw digital images that are degraded due to issues such as lack of resolution, motion and blurs	Combining super resolution (SR) and automated crack detection networks as the end-to-end data interpretation network	A deep super resolution crack network (SrcNet), which has 24% better crack detectability in comparison to the crack detection results using unmanned inspection robots	More validation required to widen the applicability of the proposed method
(Fiorillo and Nassif, 2020)	Detect subsurface damage of steel members in a steel truss bridge using infrared thermography (IRT)	modified deep inception neural network (DINN)	The method has 96% accuracy and 97.79% specificity. Also, the proposed method processed a thermal image covering an area of (0.120 m x 0.440 m) in only 55 s, while ultrasonic pulse velocity (UPV took two hours.	This method is not able to detect small or very low subsurface damages

(Ali and Cha, 2019)	Overcome the challenge of traditional CNN with bounding boxes to localize the defects, which is not capable of effectively locate detects and quantify them.	An instance level recognition and quantification approach based on Mask R-CNN	Results show 90.0%, 90.8% average precision (AP) for the bounding box and mask, respectively. The developed method can recognize bugholes on the concrete surface images, and can directly output the area and maximum diameter of the bughole, which reflect excellent bughole detection and quantization performance.	The method is not able to detect multiple damage types
(Wang et al., 2019)	Automatically monitor whether construction personnel are wearing hardhats and identify the corresponding colours (e.g. blue, white, yellow, and red)	A one-stage system based on convolutional neural network		Higher accuracy is needed for the small-scale hardhats detection
(Lei et al., 2019)	Detect buried objects from GPR profiles automatically	Combining Faster R-CNN with the DA strategy, which helps to increase the volume and variety of the training data	The proposed algorithm is more accurate and robust in terms of real-time detection and localization of buried objects in comparison to GPR	The proposed requires further validation to be applied for fitting hyperbola and estimating the peak of target
(Huynh et al., 2019)	Detect loosened bolts in critical connections	Combining a regional convolutional neural network (RCNN)-based deep learning algorithm and the Hough line transform (HLT)-based image processing algorithm	The algorithm can overcome challenges with the existing vision-based bolt-loosening methods such as the ability to identify bolts in images captured under an arbitrary shooting angle	The shooting angle for images should not go beyond 40 degrees to ensure the accuracy of the detection results

(Kim and Cho, 2019)	Develop a framework that identifies and quantifies cracks for concrete structures	Using mask and region-based CNN (Mask R-CNN)	Detects most of the cracks 0.3 mm or wider and quantifies cracks with widths of 0.3 mm or more with errors less than 0.1 mm	Cracks less than 0.3 mm widths show relatively larger error due image resolution
(Yu et al., 2019)	Develop a non-intrusive method to monitor the whole-body physical fatigue	Computer vision for construction workers using an RGB camera	3-step method for physical fatigue assessment of joint-level physical fatigue assessments non-intrusively and automatically	The method requires to measure the mass of materials or equipment to be able to perform properly, which limits the method's applicability in real construction projects
(Li et al., 2019)	provide pixel-level detection of four concrete damages: cracks, spalling, efflorescence, and holes.	Using a Fully Convolutional Network (FCN)	The performance of the trained FCN was compared with the SegNet-based method and it was showed that FCN-based method has a better performance of detection results of damages and FCN requires smaller size of trained model of the FCN compared to the SegNet	The inability to detect the depth of damages
(Liang, 2019)	Develop an approach for post-disaster inspection of the reinforced concrete bridge	Convolutional neural network for image classification, object detection, and semantic segmentation	Three-level image-based approach for post-disaster bridge inspection. The three levels are for the system-level failure analysis, the structural component-level detection, and local-level damage localization.	Further investigation is required to enable post-disaster autonomous inspection for near-real time damage detection and assessment
(Bao et al., 2019)	Review of the state of the art of data science and engineering in SHM	Literature review	Machine learning, deep learning, and Computer vision techniques can be extensively applied in SHM because they provide efficient algorithms to automatically identify cracks using big data from monitoring	Evidence of findings need to be applied in real operational scenarios

(Ni et al., 2019)	Automate crack extraction quickly and accurately at a pixel level in civil structures	convolutional feature fusion and pixel-level classification	New image-based structural damage detection and segmentation method at the pixel level, called the CDN, identifies cracks accurately and rapidly in images, which unlike some other methods does not need hand-designed low-level features	More autonomous toward detecting other damage types and segmentation from images of any size need to be considered
(Atha and Jahanshahi, 2018)	Detect corrosion of a sliding window over an image.	Two state-of-the-art CNN architectures, ZF Net and VGG16, were evaluated and compared to three proposed CNNs, Corrosion7, Corrosion5, and VGG15, for corrosion detection.	CNNs outperforms the previous state-of-the-art corrosion detection approaches	The type of corrosion cannot be identified, and the amount of corrosion cannot be measured
(Pan et al., 2018)	Extract structural information that determine conditions of the complex structures with uncertainties	using the deep Bayesian Belief Network Learning (DBBN)	DBBN could accurately determine the structural health state in terms of damage level to the conventional shallow learning Support Vector Machine;	Larger database size is needed
(Xu et al., 2018)	Identify and extract fatigue cracks from images containing complicated background on a steel structure surface	Constructing a deep learning network consisting of multiple processing restricted Boltzmann machine (RBM)	The capability of correct identification decreases for the images with low resolution	Multiple-scale deep learning is required for crack identification from images with various resolution

3. Convolutional Neural Networks (CNN) for crack detection

Amongst many of the reviewed conventional deep learning architectures, Convolutional Neural Network (CNN) is widely known for their capability of image processing, especially for applications that require image matching of width, height and depth (Krizhevsky et al., 2012). Ren et al. (2020) detected cracks with a deeper deep learning network, further improving the accuracy of crack detection. Another study by Kumar et al., (2020) developed a vision-based method using a deep architecture of convolutional neural networks (CNNs) for detecting concrete cracks without calculating the defect features. The designed CNN is trained on 40 K images of 256 × 256-pixel resolutions to detect cracks by classifying each region separately. Chuang et al. (2019) pre-processed the image by Naive Bayes classifier and then identified cracks with the CNN. Zhu and Song (2020) employed a Deep Convolutional Neural Network (DCNN) trained on the 'big data' ImageNet database, which contains millions of images, and transfer that learning to automatically detect cracks in Hot-Mix Asphalt (HMA) and Portland Cement Concrete (PCC) surfaced pavement images that also include a variety of non-crack anomalies and defects. Hoang et al. (2018) compared a CNN model with metaheuristic optimized edge detection algorithm. They showed that the performance of CNN was significantly better than edge detector. A later study by Ye et al. (2019) put forward a structural crack detection method based on CNN, which divides the image and processes it with deep NN and random forest.

However, the region-based methods can only provide information about the existence of cracks and rough shape and location depending on the size of regions. The value of crack detection decreases if the accurate pattern and location of the cracks cannot be given. Liang (2019) introduced a CNN approach for detecting concrete columns surface cracks or spalls. To overcome this issue, pixel-level crack detection methods are studied, for instance, the investigation conducted by Fan et al. (2019) improved the detection accuracy to 92.08% through the integration between the edge optimization algorithm and the CNN. Ni et al. (2018) proposed a convolutional neural network-based framework to automatically extract cracks quickly and accurately at a pixel level, through convolutional feature fusion and pixel-level classification. Liu and Zhang (2020) presented a novel context-aware deep convolutional semantic segmentation network to effectively detect cracks in structural infrastructure under various conditions. The proposed method applies a pixel-wise deep semantic segmentation network to segment the cracks on images with arbitrary sizes without retraining the prediction network. Meanwhile, a context-aware fusion algorithm that leverages local cross-state and cross-space constraints is proposed to fuse the predictions of image patches Won et al. (2020) adopted U-Net to detect the concrete cracks. Focal loss function is selected as the evaluation function, and the Adam algorithm is applied for optimization. The trained U-Net is able of identifying the crack locations from the input raw images under various conditions (such as illumination, messy background, width of cracks, etc.) with high effectiveness and robustness. Fan et al. (2020) develops a robust method for crack detection using the concept of transfer learning as an alternative to training an original neural network.

Three standard deep learning methods of training a crack classifier using 1) a shallow convolutional neural network built from scratch, 2) the output features of the VGG16 network architecture previously trained on the general ImageNet dataset, and 3) the fine-tuned top layer of VGG16 are investigated. Data augmentation is used to reduce overfitting caused by the limited and imbalanced training dataset. The image dataset includes both fatigue test photographs and actual inspection photographs captured under uncontrolled distance, lighting, angle, and blurriness conditions. Zhu and Song (2020) developed a weakly supervised network for the segmentation and detection of cracks in asphalt concrete deck. Firstly, the data were differentiated by the autoencoder, and the unlabeled data features were highlighted, so that the original data autonomously generate a weakly supervised start point for convergence. Secondly, the features were classified by k-means clustering (KMC). Thirdly, the cracks in the bridge deck defects images were subjected to semantic segmentation under weak supervision. A dataset of six types of defects on asphalt concrete bridge deck which was set up the defects in the dataset were labelled manually. A recent research was found which utilizing cycle-consistent generative adversarial learning for crack detection (Nath et al., 2020). In this study authors proposed a self-supervised structure learning network which can be trained without using paired data, even without using ground truths (GTs); this is achieved by training an additional reverse network to translate the output back to the input simultaneously.

4. Methodology

The objective of the current study is to present a workable solution and explore its practicality in a real-life setting. As argued by (Yin, 1981), an exploratory case study is the most workable method for implementing such context-dependent studies. In that sense, a case study is like simulation and experiment. Referring to the studies (see table 1) mentioned in the previous sections, majority of the studies lacked empirical application of the tools developed, and also the level of accuracy has relative reliability which would pose some difficulty in applying for other contexts. The main difference is that a case study tests a phenomenon in its real-life setting, where an experiment deliberately separates a phenomenon from its context (Yin, 1981). An illustrative case study was used to check the validity, reliability and scalability of the proposed solution (deep learning CNN model). Figure 1 shows the adopted process in order to develop a new CNN model to detect and classify highways cracks. The process begins by collecting images of different types of highway cracks (n=4663), then classifying these images to three categorises, namely, vertical cracks' 'horizontal and vertical cracks' and 'diagonal cracks. In order to check the most appropriate parameters to develop and tailor a special CNN model for highway cracks, four pre-trained CNN models were selected and applied to the three categorises of images. Subsequently, evaluating the capable points/parameters of each pre-trained model and use these parameters to develop a tailored CNN model to detect and classify highway cracks with possible maximum accuracy.

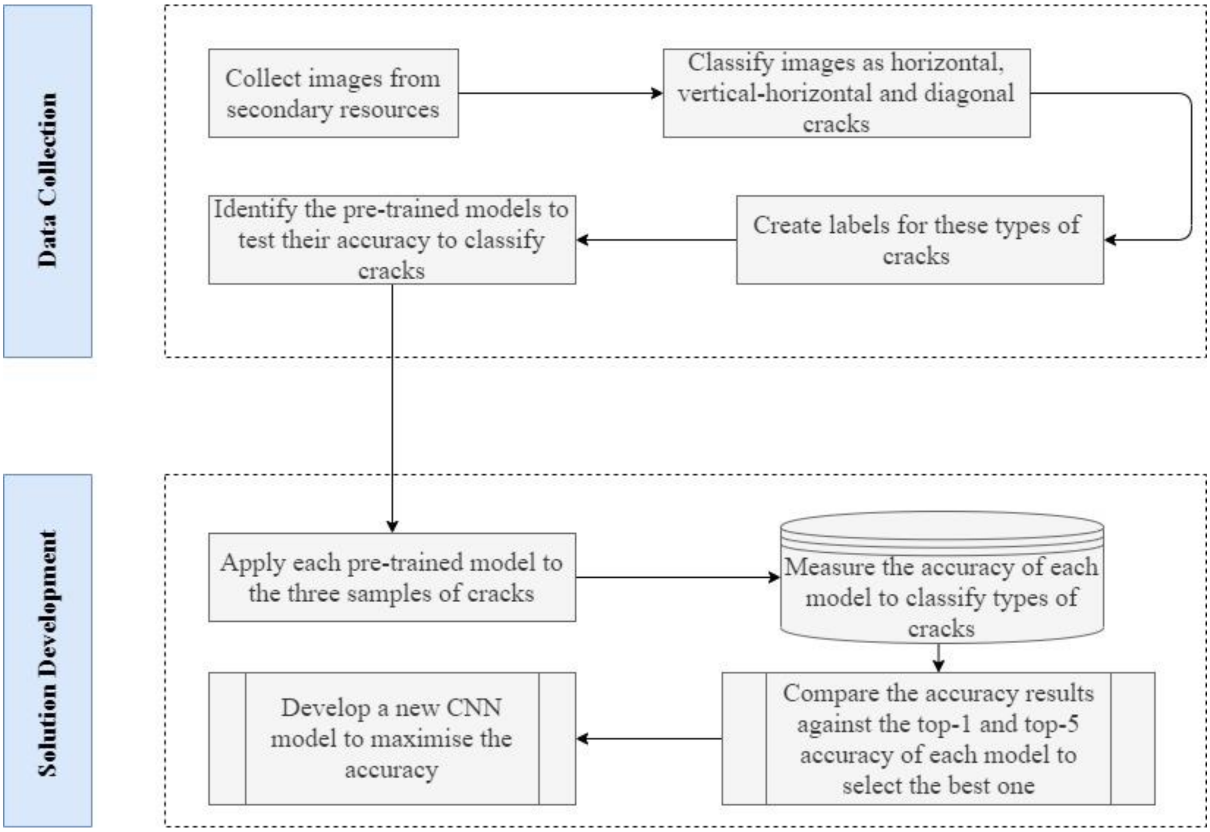


Figure 1. The logic and design of the research process

5. Data collection and analysis

Three sets of cracks images were collected as secondary data (see Figure 2). Size of samples were 'vertical cracks around 1359', 'horizontal and vertical cracks around 2184' and 'diagonal cracks around 1120'. After importing these images and classify them into Matlab platform, four pre-trained models, namely, AlexNet, VGG16, VGG19, GoogleNet. The images shows that the more images that are embedded as part of deep learning, the higher the accuracy will be achieved. In other words, this will support, not only identifying type of cracks, but also provide more accurate classification of the cracks.

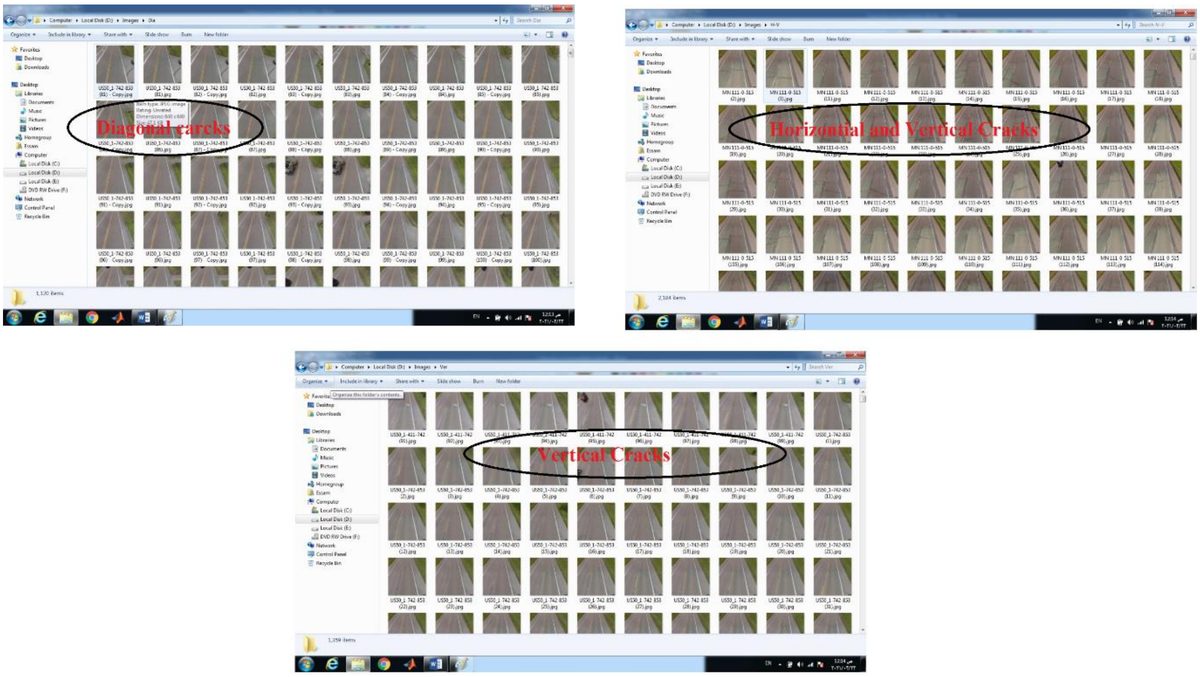


Figure 2. Used samples of highway cracks.

5.1.Comparison of Pre-trained Deep Learning Models

Figure 3 shows the process of defining the categorises of cracks, which are Dia (Diagonal), Ver (Vertical), H-V (Horizontal-Vertical). Subsequently, these defined categorises of cracks should be classified as training and validation sets so that all pre-trained CNN models will be applied and tested using these identified sets (70% for training and 30% for testing). It shows how the applied algorithm both learns from the data and classify type of cracks, which is part of the investigation in this paper.

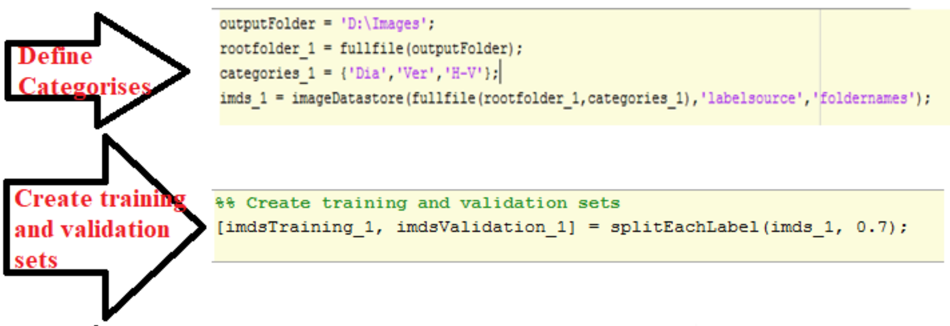


Figure 3. Define categorises and create raining and validation sets codes.

Four models were selected as shown in Table 2 to test their accuracy in classifying and identifying cracks as presented in the methodology section. In order to check the reliability of the collected data in corresponding to the accuracy of pre-trained models, the accuracy percentage should be placed between the top-1 and top-5 accuracy percentages. Accuracies results in Table 2 reveals that the quality of images were very high as the accuracy of all models are above the averages between top-1 and top-5 and the accuracy of the samples exceeded the top-5 for the pre-trained AlexNet model around 3% and by 0.2% for the GoogleNet model. The accurate model here is the GoogleNet model as the accuracy is 89.08% and it is higher than AlexNet by 1.26%. Therefore, GoogleNet is the best model to be employed for these types of distresses in highways. Results in Table 2 confirms that all these pre-trained CNN models can give accuracy more than 85% to classify the type of cracks such as horizontal, vertical-horizontal and diagonal. The large sample sizes for all types of cracks enabled to increase the accuracy of all pretrained models and once new set of data entered, the system will be able to classify new images of cracks regardless of the size and number of images, therefore, the decision maker can scan hundreds of kilometres of highway and import images to the system to determine percentages of each type of cracks in order to start the maintenance process.

Table 2. Pre-trained deep learning models

CNN Model	Accuracy	Accuracy ranges (top 1 to top 5)
AlexNet	87.83 %	63.3% to 84.6%
VGG16	85.14 %	74.4% to 91.9%
VGG19	85.93 %	47.5% to 92%
GoogleNet	89.09 %	68.93 % to 88.9%

5.2.Proposing and Evaluating a New CNN Model

Figure 4 depicts the created codes of the proposed CNN model-based highway cracks including the proposed layers, the training options to define ‘optimization algorithm, mini-batch size, learning rate, validation frequency, and max Epochs’, and codes to train the network and compute accuracy of the created CNN model at different learning rates in order to reach the maximum optimised accuracy. The below figure, indeed, explains the three steps followed for the CNN model. Step 1 defines the layers and the parameters associated with each of the layers; step 2 explains the training options to identify optimisation algorithm, learning rate, and mini-batch size; step 3 explains the training of the model based on both steps 1 & 2.

Figure 4. Codes of the proposed CNN-based highway cracks model

Figure 4 shows the details of the proposed CNN model in terms of type of layer, activations and learnable. CNN includes neurons with learnable weights and biases. Numerous inputs are received by neurons by which a weighted sum of those inputs is considered. Finally, the weighted sum of inputs passes through an activation function to provide an output.

Each layer of a CNN has two kinds of parameters: weights and biases. The number of parameters can be computed for each layer as follows;

$$W_c = K^2 \times C \times N$$

$$B_c = N$$

$$P_c = W_c + B_c$$

Where W_c is the number of weights, B_c is the number of biases, N is the number of kernels, C is the number of channels of input images, and P_c is the total number of parameters of a layer.

Figure 5 also provides the stride and padding of convolutional and pooling layers. Stride determines the number of pixels shifts over the input matrix. When stride equals "1", kernels will move by 1 pixel at a time. Padding is the process of adding layers of zeros to the input images. The figure (figure 5) comprehensively provides detailing of each of the layers in terms of activations. This will support identifying that the model is functioning systematically in a sense that the outcomes from a particular layer can form the inputs for another layer.

	Name	Type	Activations	Learnables
1	imageinput 224x224x3 images with 'zerocenter' normalization	Image Input	224×224×3	-
2	conv_1 16 3x3x3 convolutions with stride [1 1] and padding [1 1 1 1]	Convolution	224×224×16	Weights 3×3×3×16 Bias 1×1×16
3	batchnorm_1 Batch normalization with 16 channels	Batch Normalization	224×224×16	Offset 1×1×16 Scale 1×1×16
4	relu_1 ReLU	ReLU	224×224×16	-
5	maxpool_1 2x2 max pooling with stride [2 2] and padding [0 0 0 0]	Max Pooling	112×112×16	-
6	conv_2 32 3x3x16 convolutions with stride [1 1] and padding [1 1 1 1]	Convolution	112×112×32	Weights 3×3×16×32 Bias 1×1×32
7	batchnorm_2 Batch normalization with 32 channels	Batch Normalization	112×112×32	Offset 1×1×32 Scale 1×1×32
8	relu_2 ReLU	ReLU	112×112×32	-
9	maxpool_2 2x2 max pooling with stride [2 2] and padding [0 0 0 0]	Max Pooling	56×56×32	-
10	conv_3 64 3x3x32 convolutions with stride [1 1] and padding [1 1 1 1]	Convolution	56×56×64	Weights 3×3×32×64 Bias 1×1×64
11	batchnorm_3 Batch normalization with 64 channels	Batch Normalization	56×56×64	Offset 1×1×64 Scale 1×1×64
12	relu_3 ReLU	ReLU	56×56×64	-
13	fc 3 fully connected layer	Fully Connected	1×1×3	Weights 3×200704 Bias 3×1
14	softmax softmax	Softmax	1×1×3	-
15	classoutput crossentropyex with 'Dia' and 2 other classes	Classification Output	-	-

Figure 5. The proposed CNN model parameters

Classification Accuracy of the Proposed Model

The following Table 3 illustrates the values of various hyper parameters of the proposed model. These parameters were selected based on the comparison between pre-trained models in order to determine the capabilities of each one to detect small cracks from a good quality set of images.

Table 3. The values of various hyper parameters for the proposed model

Parameter	**Value**
Weight decay	5×10-4
Momentum	0.9
Iterations per epoch	73
Maximum iterations	365
Mini-batch size	32
Maximum epochs	5

5.3.Comparing Between Different Optimisation Algorithms to Enhance the Accuracy

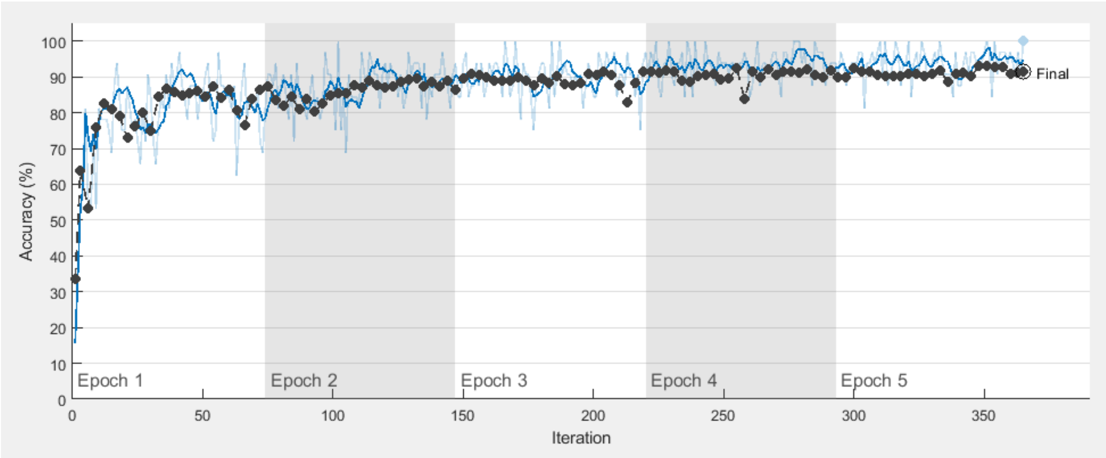
Three optimisation algorithms were applied to the proposed CNN model in order to enhance the accuracy as seen in Table 4. It can be seen that accuracies at different learning rates are ranged from 82.54% to 97.62% and this is higher than the best accurate pre-trained model (GoogleNet) by 8.53%. In order to check the reliability, validity and scalability of the proposed CNN model, the accuracy was measured in corresponding to three learning rates. For instance, the most accurate rate for SGDM and Rmsprop algorithms was at 0.001, while Adam algorithm the highest accuracy point was achieved at learning rate 0.0001 and this is the optimised and recommended algorithm to be used for the proposed CNN model.

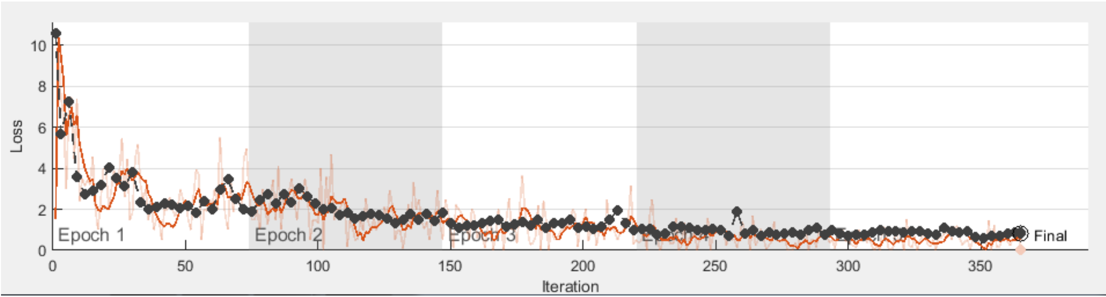
Table 4. Accuracies in corresponding to optimisation algorithms.

Optimization Algorithm	Learning Rate	Accuracy
SGDM	**0.01**	90.08 %
	0.001	97.42 %
	0.0001	97.32 %
Rmsprop	**0.01**	88 %
	0.001	95.24 %
	0.0001	82.54 %
Adam	**0.01**	91.47 %
	0.001	92.56 %
	0.0001	**97.62 %**

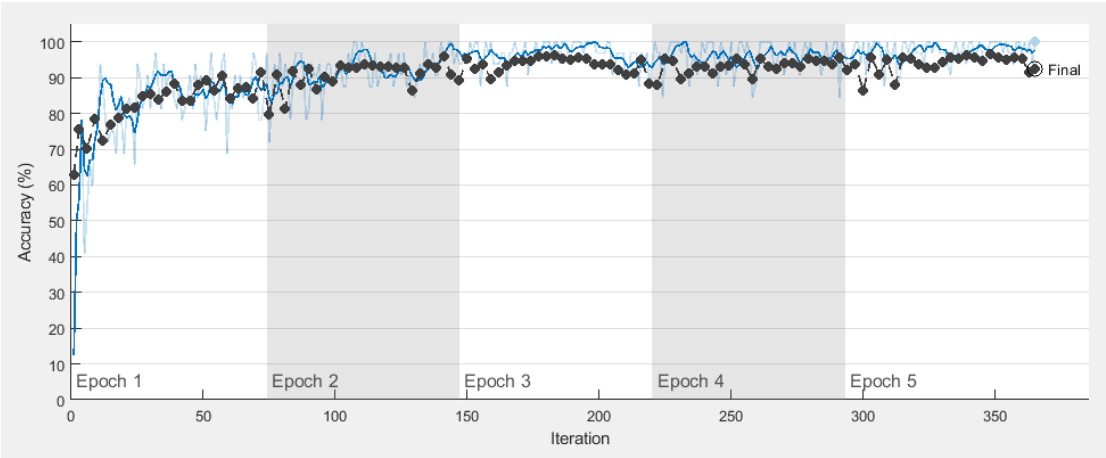
Figure 6 shows the curves of accuracy against diffent epoch (iterations) and loss values against different iterations to reach the final point for the recommended opimisation algorithm, which is Adam. learning rates as presented in Table 4. The learning rates (0.01, 0.001 and 0.0001) illustrated in figure 6 as well as the maximum-epochs (refer back to training options in figure 4) would support identification level of accuracy and how to changes. This can perhaps support how graphically the training of CNN model would change versus iterations (at each epoch).

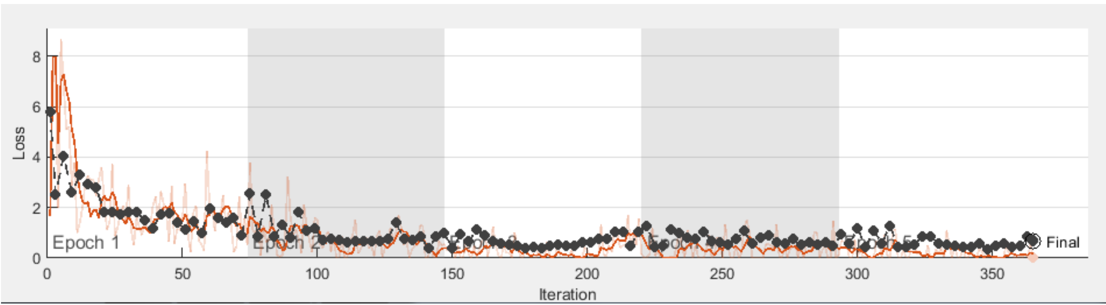
LR0.01:





LR0.001:





LR0.0001:

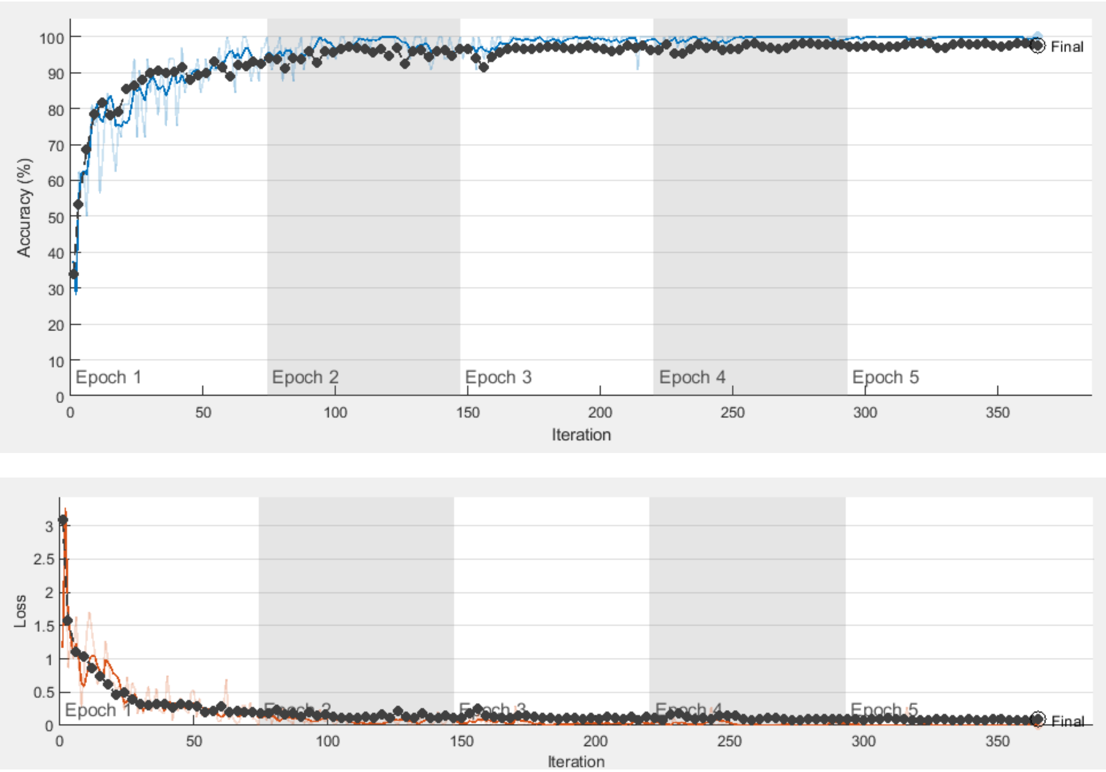


Figure 6. Adam algorithm accuracy results in corresponding to learning rate.

6. Significance and Contribution

The proposed CNN-based highway cracks are distinguished from existing pre-trained models based on the following aspects:

- The parameters were built based on the revealed capabilities of four pre-trained CNN models to detect highway cracks. Therefore, the proposed CNN-based highway model gets benefits from the observation from testing these pre-trained models using the same samples.
- The potential users will be able to use this model to scan a long highway and evaluate its health case in a few minutes since the proposed CNN was built and tested using a large size sample of high quality images and accuracy were very high. Therefore, the poor quality images will be also detected at a relative lower accuracy level. However, the model will be workable under different scenarios and a wide range of inputs.

- The proposed CNN-based highway cracks were tested using different optimisation algorithms at different learning rates. Therefore, its accuracy will correspondingly increase with adding more images. This means that users such as highways agencies can use it for their highways and the model will be automatically adjusted to their types of cracks, quality of images and other criteria. As such, the proposed CNN-based highway cracks are scalable model compared to the pre-trained CNN model that were used to detect highways cracks in similar research.
- The accuracy of the created CNN-based highway cracks is higher than the top-5 accuracy of the tested pre-trained CNN models as the highest top-5 accuracy for VGG19 is 92%, meanwhile the accuracy of the proposed CNN model is higher than 97%. This goes beyond many conventional Neural Network-based approaches, as deep learning would allow more accurate outcomes which corresponds to the amount of data provided.

7. Conclusion

To sum up, this study aimed at developing a CNN model that supported the detection and classification of highway cracks. Following an extensive literature review, the accuracy of four pre-trained CNN models (i.e. AlexNet, VGG16, VGG19, GoogleNet) were tested to classify and detect types of cracks for highways. Results showed that the accuracies of all pre-trained models were higher (97.72%) than averages and the computed accuracies for AlexNet and GoogleNet models by more than 5%. After analysing the capabilities of each pre-trained CNN models, a CNN model, which is tailored for highway cracks characteristics, is proposed. The accuracy was computed for three optimisation algorithms at three different learning rates in order to reach the maximum optimal accuracy. For the created CNN model, the maximum accuracy was achieved by Adam's optimisation algorithm at learning rate (0.001) by 79.62%.

The proposed CNN-based highway model is valuable for highways agencies to scan long highways by importing images to the created CNN-based highway model and the model will classify cracks. This is to enable highways agencies to start the maintenance activities and divide the road to specific sections according to types and density of cracks. This means that users such as highways agencies can use it for their highways and the model will be automatically adjusted to their types of cracks, quality of images and other criteria. For future studies, other samples of various types of cracks can be added to the proposed CNN model to enable it to detect a wide range of highway cracks. Moreover, the created CNN-based highway cracks will be included in an integrated maintenance system that will consider a wide range of highway distresses, as well as, evaluating the severity degree of cracks.

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