SOHAIB, M., HASAN, M.J., CHEN, J. and ZHENG, Z. 2024. Generalizing infrastructure inspection: step transfer learning aided extreme learning machine for automated crack detection in concrete structures. *Measurement science and technology* [online], 35(5): AI-driven measurement methods for resilient infrastructure and communities, article number 055402. Available from: https://doi.org/10.1088/1361-6501/ad296c

Generalizing infrastructure inspection: step transfer learning aided extreme learning machine for automated crack detection in concrete structures.

SOHAIB, M., HASAN, M.J., CHEN, J. and ZHENG, Z.

2024

Journal **XX** (XXXX) XXXXXX https://doi.org/XXXX/XXXX

Generalizing Infrastructure Inspection: Step Transfer Learning Aided Extreme Learning Machine for Automated Crack Detection in Concrete Structures

Muhammad Sohaib[1,2], Md Junayed Hasan[3], Jianxin Chen[4], and Zhonglong Zheng[1]

Author Name[1], Author Name[2] and Author Name[1,2]

[1] School of Computer Science and Technology, Zhejiang Normal University, Jinhua 321004, China.
[2] Zhejiang Institute of Photoelectronics and Zhejiang Institute for Advanced Light Source, Zhejiang Normal University, Jinhua 321004, China
[3] National Subsea Centre, Robert Gordon University, Aberdeen, AB21 0BH, U.K.
[4] School of computer science, Jiaxing University, Jiaxing 314001, China.

E-mail: zhonglong@zjnu.edu.cn

Received xxxxxx
Accepted for publication xxxxxx
Published xxxxxx

Abstract

Identification of damage and selection of a restoration strategy in concrete structures is contingent upon automatic inspection for crack detection and assessment. Most research on deep learning models for autonomous inspection has focused solely on measuring crack dimensions, omitting the generalization power of a model. This research utilizes a novel step transfer learning aided extreme learning machine (STELM) approach to develop an automatic assessment strategy for surface cracks in concrete structures. Step transfer learning (STL) is helpful in mining generalized abstract features from different sets of source images, and extreme learning machine (ELM) helps the proposed model overcome the optimization limitations of traditional artificial neural networks. The proposed model achieved at least 2.5%, 4.8%, and 0.8% improvement in accuracy, recall, and precision, respectively, in comparison to the other studies, indicating that the proposed model could aid in the automated inspection of concrete structures, ensuring high generalization ability.

Keywords: concrete cracks detection, Concrete structures, Extreme learning machine, Infrastructure step transfer learning, Structural health monitoring, Structural integrity

1. Introduction

When constructing structures like bridges, buildings, highways, and payments, concrete is a common material utilized in the process. The structures made of concrete deteriorate over time as a result of adverse environmental conditions, overloading, and material degradation [1], [2], [3]. Microcracks to larger cracks are the initial symptom of deterioration in concrete structures. The propagation of the cracks has the potential to reduce the durability of a concrete structure and jeopardize its skeletal support [4], [5]. These gaps allow the entry of water and toxic chemicals into the structure. Rebar corrosion may be triggered if the cracks extend to the level of the rebars. The safety and use of the concrete structure can be compromised by disintegration and spalling of the concrete that might result from the development of corrosion or fire [6], [7], [8]. Concrete structure inspection for crack detection is essential for detecting damage and assessing conditions [9], [10], [11]. In order to avoid significant damage and maintain public safety, it is essential to detect cracks before choosing the best repair strategy.

A manual visual inspection is performed to detect cracks in the surface of a concrete structure. However, it takes a lot of time, requires a lot of work, and puts the safety of the inspectors at risk [12], [13]. This approach is also dependent on the qualifications, experience, and abilities of the in charge of the inspection. Consequently, researchers have explored and developed various non-invasive techniques to evaluate the condition of concrete structures and analyze the outputs to asses the behavior of the reinforcing elements under different dynamic loading scenarios [14], [15]. The structures may experience long-term loading, such as their own weight, or dynamic loading, including environmantal deterioration and earthquackes [16]. To develop automated and non-invasive techniques of inspection machine learning algorithms have been investigated using multimodal data to get around these constraints. These non-invasive techniques are becoming more and more crucial in the maintenance of intelligent facilities due their affordability and user friendly attributes. Moreover, automated inspection for cracks has the benefit of being efficient as it is less labor intensive as well as lowers the risk of workplace accidents [17], [18]. Moreover, since this assessment is determined by a computerized algorithm, it may be more impartial and trustworthy. Numerous studies have looked into the viability of automated inspection for crack detection using deep learning and digital image processing techniques (DIPT) in concrete structures. In this regard, a vision-based approach is suggested for crack and density assessment in concrete structures using a fully connected network (FCN) [19]. A VGG16 network was used as the foundation of the FCN encoder because it outperformed InceptionV3 and ResNet in the detection of cracks in images. The entire encoder-decoder FCN architecture was trained, validated, and tested end-to-end, and on the training, validation, and test sets, which yielded 90% of both the F1 and average precision scores. However, the proposed method lacked in estimating the crack sizes, especially when the test image contains numerous noisy crack-like characteristics. Similarly, Abdel-Qader et al., [20] presented a DIPT-based edge recognition approach for concrete crack detection. Algorithms for edge recognition were examined for crack identification in concrete structures that provided a maximum accuracy of 86%. The sharp shift in brightness brought on by texture in the image, however, makes edge recognition systems vulnerable to noise, shadows, defects, and illumination. A convolution neural network (CNN) model was proposed to solve a binary classification problem, i.e., to detect cracks in concrete structures [21]. An integrated CNN model incorporating regression models, i.e., RF and XGBoost, was presented for predicting the depth of cracks in concrete structures based on the features extracted through a CNN model. The suggested model achieved an accuracy of 99.9% when tested on a public dataset containing images of cracks in concrete structures. Additionally, when the model was tested with data from a damaged RC slab present in the laboratory it demonstrated 93.7% accuracy. Moreover, the performance also deteriorated when tested with unseen data as it could provide only 93.7 % of accuracy. For crack detection, a percolation-based image processing method was proposed [22]. Macro cracks could be recognized by the approach since it is dependent on the size and brightness of the cracks, while small, undefined cracks were mistaken for noise. Furthermore, the implementation of an image binarization technique allowed the detection of cracks as well as the estimation of their widths on a concrete surface. Although crack widths were predicted with an error of less than 11%, the approach was unable to identify minor cracks that were present in the blurred images. To find microscopic cracks and determine their breadth and length, Kim et al. [23] used a hybrid image binarization technique. However, the absence of a defined approach to establish a threshold and pick the appropriate parameters for feature extraction makes it a time-consuming, ineffective, and expensive operation.

Deep learning has been explored to overcome the limitations of DIPTs used for automated crack detection in concrete structures [24], [25], [26], [27]. Due to its hierarchical architecture and non-linear transformations used in the layers, it can automatically extract features from images. Therefore, deep learning techniques are more beneficial than traditional DIPTs as these techniques are robust and can accurately detect defects [28], [29]. A deep CNN has a promising performance in image classification tasks as it can distinguish and classify images with high accuracy and precision [30], [31]. Assessing the state of a concrete building requires automatic crack detection as it is crucial to evaluate its structural integrity. To prevent substantial damage to the concrete structure, it is also helpful to choose and use the proper repair procedure such as surface coatings or sealers, grouting or epoxy injection, or a comprehensive repair using replacement concrete. Concrete crack inspection and quantification have been performed using CNN and integrated CNN to overcome the shortcomings of the conventional DIPTs [32], [33], [34]. These algorithms, however, have only been concerned with identifying cracks and figuring out their size, shape, location, orientation, and depth. To the best of my knowledge, there are no automated inspection methods that can address the generalization issue normally encountered by the automated inspection model. To address this issue, a step transfer learning added extreme learning machine (STELM) is proposed in this work to boost the generalization power of the crack detection model. This study first seeks to close this gap by investigating the potential of utilizing a double-step transfer in combination with a conventional transfer learning process to create a more informative and generalized pool of abstract features suitable for crack detection in concrete structures. Next, an extreme learning machine (ELM) is applied to the pool of abstract features to classify the data with high generalization power. The contributions of this study are described as follows.

1- Improving the learning capability of the concrete crack detection model by combining a double-step transfer learning concept into a basic transfer. In this, abstract features are explored from different image sources by transferring knowledge in two steps utilizing separate pre-trained models, hence, mitigating the overfitting problem.

2- Creation of a hybrid feature pool of abstract features containing diverse information that is useful for the underlying classifier to accurately classify the data.

3- Formation of a powerful classifier with enhanced generalization power by the application of extreme learning method for the data classification to overcome the basic limitations of traditional neural networks.

The rest of the paper is organized as follows: Section 2 is related to the technical background of the algorithms used in this work. Section 3 defines the methodology adopted to develop an automated crack detection model with better generalization power. Section 4 is about the explanation of the dataset description and experimental setup. Section 5 presents the results and analysis of the proposed model. In section 6 the whole work has been concluded.

2. Technical Background

To prevent a concrete structure from further damage and to ensure public safety automatic assessment of cracks is a vital process. This research aims to provide an automatic crack detection mechanism with better generalization power while ensuring efficiency, rationality, and accuracy of the process and results. To establish a complete framework with high generalization power for crack detection and depth prediction, we investigate the use of deep learning techniques including, double-step transfer learning and extreme learning. The technical details about these techniques are provided in the following subsections.

2.1 Double Step Transfer learning

Double step transfer learning (DTL) goal is to complete a learning task T_{tr} on the target domain D_t with a few labeled samples by recycling information learned in a previous task T_{sr} on the source domain D_{sr}. In the conventional transfer learning (TL) approach, T_{sr} is a generic task, for instance, target identification on ImageNet. The instance-based transfer learns about the distribution of samples in D_{sr} through the following mapping function.

$$DT = f\big((D_{sr} \rightarrow T_{sr}) \times (D_{tr} \rightarrow T_{tr})\big) \rightarrow f\big((D_{sr} \rightarrow D_{tr}) \rightarrow T_{tr}\big).$$

Contrary to that, network-based transfer learning updates model weights and learnable parameters in T_{sr} through the following mapping function.

$$DT = f\big((D_{sr} \rightarrow T_{sr}) \times (D_{tr} \rightarrow T_{tr})\big) \rightarrow f\big(D_{tr} \rightarrow (T_{sr} \rightarrow T_{tr})\big).$$

However, it is challenging to obtain a good D_sr dataset for the surface cracks task due to the specific morphological properties of the cracks present in the structures, which make it very different from the domains frequently used in target detection. This means that conventional TL approaches based on features extracted from generic images are not adequate for crack identification in concrete structures. The double-step deep transfer strategy suggested in this research aims to combine the benefits of the aforementioned methods.

Images that share the same morphological features as cracks on concrete structures are easier to find than actual cracks. To facilitate more efficient information transfer, a subset domain D'_{sr} from D_{sr} can be conceptualized using images that can make the domain portray similar properties to cracks in concrete structures, i.e., the target domain D_{tr}.The D'_{sr}, which is an updated domain of origin, can then be leveraged to complete the two-stage transfer as follow: the instance-based transfer can be adopted to vigorously extract features in the incipient step, whereas, in the second transfer stage network-based transfer can be used to update the learnable parameters and weights from the original network to D_{tr}. Next, a different real-world concrete crack dataset is used to fine-tune the network, resulting in a deep network with a superior abstract feature pool. This process can be mathematically represented as follows.

$$f\big((D_{sr} \rightarrow T_{sr}) \times (D_{tr} \rightarrow T_{tr})\big) f\Big(\big((D_{sr} \rightarrow D'_{sr}) \rightarrow T'_{sr}\big) \rightarrow\ (D_{tr} \rightarrow T_{tr})\Big)$$

The two-stage transfer method across domains can be applied to many tasks with insufficient training samples if the appropriate D'_s are selected in the first stage. Good explainability is a feature of both the training samples and the model's weights/parameters, which undergo separate transfer phases.

2.2 Residual Neural Network

It is generally assumed that the performance of a network is directly proportional to its depth in the presence of a big data [35], therefore, in the field of computer vision, ever-deeper neural networks are used. However, due to the known gradient vanishing problem, training a deeper network is challenging [36]. Kaiming et al., presented a straightforward approach to this issue and named it a residual neural network (ResNet) [37]. ResNet is a training framework that makes it simpler to train networks that are far more complex than earlier methods. The unexpected results of experiments showing that adding additional layers increases training error provided the impetus for this. Theoretically, the modeling skills of Neural Networks should improve with an increase in the number of layers, and the deeper networks should result in no greater training error. The authors hypothesize that this is due to the fact that gradients disappear after being transmitted via a large number of layers. The authors advocated adding shortcut connections using identity functions rather than directly fitting the stacked layer to the underlying mappings as shown in Fig.1 through the basic building block of a ResNet. Let's suppose, the original underlying mapping is denoted as $L(x)$, whereas, in ResNet fitting of nonlinear layers is done to an alternative mapping given as follows.

$$F(x) \coloneqq L(x) - x$$

This arrangement allows some of the information from prior layers to flow unfettered to later layers through the main connections. ResNet drastically increases training efficiency, as demonstrated by experiments in [reference], because gradients can propagate through multiple layers via the shortcut connection. In addition, ResNet enables the training of deeper networks, which typically results in better-performing models. In our trials, ResNets will serve as the foundation for our models.

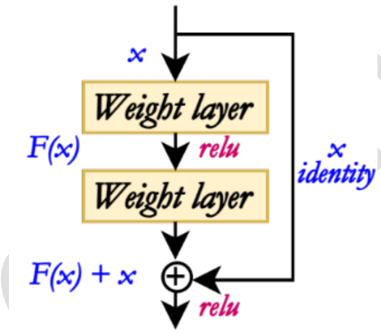


Fig.1 A basic building block of ResNet.

2.3 Extreme Learning Machine

Huang et al., presented a mathematical model for a single-hidden-layer feedforward ELM that contains N neurons in the hidden layer and provides an output through function $\;_N(\cdot)$ which is represented by the following mathematical expression [reference].

$$f_N(x) = \sum_{i=1}^{N} W_i G_i(x, w_i, b_i), \quad x, w_i \in \mathbb{R}^d, W_i \in \mathbb{R}^m, b_i \in \mathbb{R}$$

where $G_i(\cdot)$ is the activation function of the i-th hidden neuron, represents the weights and biases of the hidden layer which are generated randomly, and $W_i \in \mathbb{R}^m$ indicates the output layer weights. The following equation denotes the relationship between the function $G_i(\cdot)$, and the activation function g(·). The operation is performed on a data representation for additive neurons through a radial basis function (RBF), respectively [38].

$$G_i(x, w_i, b_i) = g(w_i x + b_i) \,\&\, G_i(x, w_i, b_i) = g(b_i \|x - w_i\|).$$

The results presented by Huang et al., and Huang and Chen confirm that the ELM algorithm can effectively approximate the original data if it satisfies the following: (i) the output of the network is optimized by the least squares technique, (ii) the activation function used in neurons is not piecewise constant, and (iii) the spanning set, i.e., $\{G\ (x\ .\ w\ \ ,\ b\ ):(w\ \ ,\ b\ ) \in \mathbb{R}^d \times \mathbb{R}\}$ is dense in $N\ ^2(\mathbb{R}^n \times \mathbb{R})$.

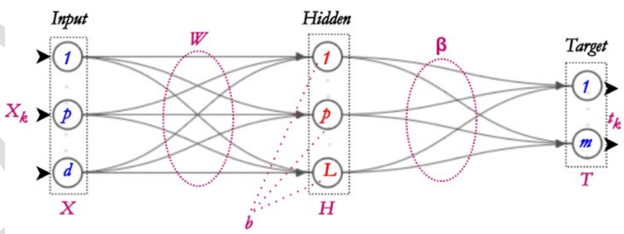


Fig.2 *An illustration of a typical extreme learning machine (ELM).*

3. Methodology

This study applies deep learning techniques, including double-step transfer learning and extreme learning, to create a robust framework (STELM) for crack detection and depth prediction. The proposed work plan is divided into two parts, as shown in Fig 3. In the first step, two pre-trained ResNet on an image dataset are used for sharing their parameters, to fine-tune according to the surface crack detection task. The pre-trained networks are fine-tuned using two different datasets containing images of concrete structures with and without cracks to create a pool of high-level abstract features suitable for the completion of the classification task. In the transfer learning step, one network is fine-tuned twice on the samples from two different datasets so that it may learn vibrant information regarding the target task. Similarly, the second pre-trained model is fine-tuned once on a single dataset of concrete crack images using the concept of traditional transfer learning. In the second step, the extracted pool of high-level abstract features is provided to the ELM algorithm to detect

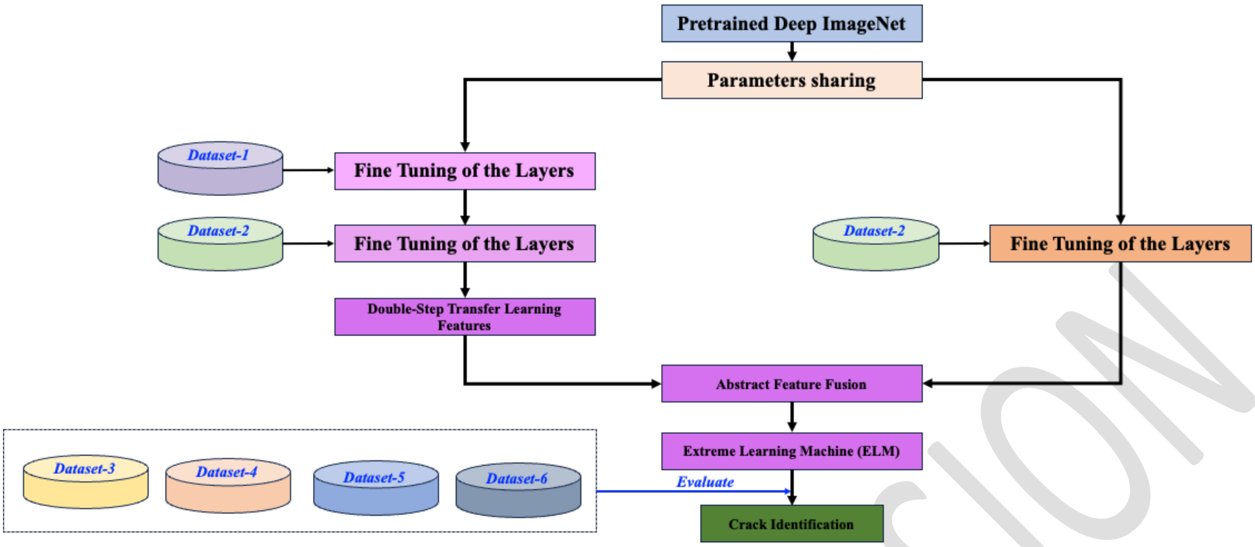


Fig.3 An illustration of the proposed step transfer learning added extreme learning machine (STELM) for the automatic detection of surface cracks in concrete structures.

cracks in unseen data samples. The advantage of introducing double-step transfer learning is to enhance the generalization capability of the designed approach for concrete surface crack detection.

1 Transfer Learning Features

In machine learning, transfer learning denotes the practice of using a pre-trained model as the basis for a new assignment. In other words, a model which is trained on one task can be used to optimize the modelling of a second, similar activity, allowing for rapid development of an algorithm. This practice is common in deep learning because through this deep neural networks can be trained in comparatively less time and with a little amount of data [39].This is useful practice since it is difficult to accumulate millions of labeled data samples for most of the real-world problems to train complex deep networks [40]. When starting something from scratch, it can be difficult to collect a huge amount of data. It is also challenging to train an adequate model with less data and yet achieve desirable results. Compared to training with a small amount of data, the results of applying transfer learning to a new task are dramatically better. Training a model from the scratch in an image or natural language processing task is uncommon due to the prevalence of transfer learning. The task under experimentation in this work is also image processing and machine learning related. So, for this reason, instead of developing an artificial neural network model from scratch, a pre-trained network is fine-tuned using double-step transfer learning. It helps to avoid the development complexity, avail the rapid convergence of the network according to the new task and mitigate the problems like overfitting while there is limited data available.

3.2 Double-step Transfer Learning Features

Generally, in transfer learning a pre-trained network is fine-tuned on a single dataset just once related to a new task. The aim is to adjust the parameters of the pre-trained network according to the new task. As a result, the parameters of the fine-tuned network are adjusted according to the new dataset, therefore, it is able to classify the new data with better precision and accuracy. In the single-step transfer learning process, a limited amount of dataset from a single source is considered to fine-tune the layer of the pre-trained network. It has shown considerable progress in overcoming the subpar performance brought on by a scarcity of training data. However, during transfer learning, it simply uses data from a single source to fine-tune the pre-train network, forgoing the benefit of mixing data from several sources. In order to fully exploit the capability of TL, an STL approach known as the double-step transfer learning (DSTL) in addition to conventional TL is adopted in this study. Through DSTL transition of knowledge from the source domain to the target domain can be significantly improvised. In this work, the source data in TL and DSTL are the ImageNet and the Concrete crack Image datasets, respectively. The target data in TL and DSTL are the images representing carks in concrete structures. First, two pre-trained ResNets models on ImageNet are retrieved and fine-tuned on two separate sets of images containing cracks in concrete structures using the instance-based TL approach. Next, on one of the fine-tuned models, a DSTL approach is applied in which the model is further fine-tuned using a set of images representing cracks in concrete structures retrieved from a different source. So, first, the conventional TL step is applied in which ImageNet is set as the source data and concrete crack images are set as the transition source data. Later, the high-level abstract features extracted from two different datasets through conventional TL and DSTL are concatenated to create a pool of abstract features more useful for the target task.

The primary focus of the first stage of instance-based TL is to initiate the weights of the network so that the primary information can be inherited from a pre-existing bank of data such as the ImageNet dataset. In order to train a deep neural network (DNN) for concrete surface crack identification the raw ImageNet is not very helpful due to differences in morphological characteristics, the proposed mechanism for transferring knowledge takes into account the degree to which the original source domain and the new source domain are similar. Images of anomalous surface defect manifestations like cracks and spalls have evident morphological characteristics that are distinct among concrete structures. The use of data that have similar visual features can enhance the learning capability of the network and can help mine and transfer more usable knowledge. It is not effective to detect cracks in concrete structures just by using common features explored in the raw ImageNet dataset. When compared to standard transfer learning, which merely recycles simple visual elements like edges, the combined high-dimensional features are more amenable to knowledge transfer because of the greater similarity between them.

In DNNs, it is common knowledge that the first layers learn to extract simple generic characteristics that can be used with any image, while the last levels represent extremely abstract and data-specific features. Fine-tuning a pre-trained DNN using relevant data to the target task, i.e., crack detection through transfer learning will take comparatively less time than developing a deep network from scratch. Moreover, the DNN is expected to have an improved ability in crack detection after the 1st-stage transfer stage as the updated weights and learnable parameters will aid in constructing a powerful feature extractor to explore distinct features.

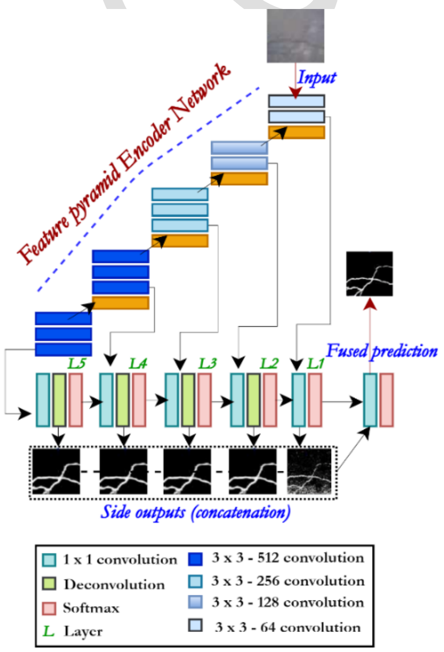


Fig.4 An illustration of the pyramid feature fusion.

In fine-tuning, most of the layers inherited from the pre-trained network are frozen to preserve D_{sr} knowledge, only the fully connected layer and a few prior hidden layers are retrained forming a pyramid encoder network to perform feature fusion in a real-world crack detection scenario as shown in Fig. 4. Before fine-tuning for crack detection in images taken from concrete structures, these pre-trained ResNets and their hyper-parameters will be employed directly as part of the new DNNs. In fine-tuning, the model converges to a network that reliably detects cracks in input images as shown in the figure. It indicates performing a double-step transfer method on powerful pre-trained networks with a relatively small amount of training data can significantly enhance accuracy, reduce training time, and cut off the need to optimize hyper-parameters.

3.3 Extreme Learning Machine

The term "artificial neural network" (ANN) is used to describe computational models that are intended to simulate biological nerve systems like the human brain. Among the most effective ANNs, feedforward neural networks (FNNs) are distinguished by the absence of a cycle in the links between their nodes. Since data is exclusively transmitted forwards through the network, this topology is known as a feedforward topology. In FNN, a neuron serves as the fundamental functional unit. Backpropagation (BP), the conjugate gradient method, and many more learning algorithms used to train feedforward neural networks (FNNs) are all variations of the classic gradient approach. Slow convergence, sensitivity to noisy data, the local minimum problem, etc. are only some of the issues that plague these kinds of algorithms. Extreme Learning Machine (ELM) is one solution to these problems because it has fewer requirements in terms of training time, guarantees a global optimum, and improves generalization in neural networks while still retaining these benefits. Extreme Learning Machine (ELM) algorithm is designed to solve the output weight problem of a single task with only one prediction error matrix. It is a fast and efficient neural network model in pattern recognition and machine learning. Therefore, to improve the overall generalization capability of the proposed surface crack detection strategy, an extreme learning machine is used to classify the abstract representation learned during the DSTL process with high precision and accuracy.

3.4 Performance Evaluation Matrices

To evaluate the effectiveness of the proposed STELM for identifying cracks in the surface of concrete structures multiple performance evaluation matrices, such as percentage of average classification accuracy (PACA) and a loss function graph, have been used in this study. Furthermore, the k-fold cross-validation technique is used during the development of the end-to-end crack detection model with setting $k = 10$. The k-fold cross-validation method helped in reducing the variance of the end results of the proposed model as well as avoiding the overfitting problem normally encountered during the training phase of a model. The PACA in classification can be determined by using the formula:

$$PACA = \frac{1}{D}\sum_{p=1}^{D}\frac{1}{k}\sum_{i=1}^{k}\frac{TruePositive_{pi} + TrueNegative_{pi}}{Total - samples_i}, where\ D = Total\ classes$$

4. Dataset Description and Configuration

In this study, three different datasets constituting surface cracks in concrete structures are used to develop and validate the generalization ability of the proposed model. A few samples from two datasets are used during the transfer learning process to fine-tune two separate pre-trained ResNet according to the target task. The fine-tuning process helped in the exploration of abstract features with distinct distribution patterns that were very useful to complete the classification task with high efficacy and precision. For the details of these datasets, see the following subsections and Fig. 5.

4.1 Structural Defects Network 2018 Dataset

The Structural defects network 2018 also known as the SDNET2018 dataset is used in the first step of the transfer learning process which is provided by Utah State University and publicly available at [41]. It is a labeled image dataset for the training, validation, and benchmarking of crack detection algorithms in concrete structures using artificial intelligence algorithms including machine learning and deep learning. The dataset is composed of over 56,000 images presenting cracked and without crack states of concrete bridge decks, walls, and pavements. The dataset features surface cracks ranging in size from 0.06 mm to 25 mm. Shadows, surface roughness, scaling, edges, holes, and background debris are just some of the obstructive elements that can be found in the dataset's photos. The image data is split into two subsets, i.e., without crack and with crack subsets. Each category has 28000 images with 256 * 256 pixels with RGB channels.

4.2 Middle East Technical University

In this work, a concept of double-step transfer learning is used to explore the advantage of transfer learning to the full extent. For this reason, once again the process of transfer learning is carried out on the finetuned network for abstract feature extraction in the concrete crack image. For this purpose, a concrete cracks image dataset is used which is provided by Middle East Technical University and retrieved from Kaggle [42]. In total, there are 40,000 images each with an RGB color channel at a resolution of 227x227 pixels in this dataset. Images with cracks have been labeled "Positive," whereas those without cracks have been labeled "Negative", with each class containing 20,000 images.

4.3 Crack-Detection-and-Segmentation Dataset for UAV Inspection

A detailed crack detection and segmentation database was created in [43] using images of cracks with a resolution of 450 × 450. Cracks in a variety of constructions, including roads, bridges, and buildings, are recorded in the database. In the whole dataset, crack detection dataset was used in this study which contained 28309 with and without caracks images. This database is used as one of the test datasets to evaluate the effectiveness of the developed double-step transfer network for crack detection in concrete structures. The purpose is to use this dataset to validate the generalization power of the network in the presence of totally unseen data samples.

4.4 The Datasets Configuration for the Experiment

The samples with and without cracks from each dataset used in the experiment are presented in Fig. 5. Furthermore, the details about the configuration of the datasets used during the training, validation and test phases are presented in Table 1. It can be seen that Dataset-1 is formed by considering 80% of the data, i.e., 44800 data samples from the SDNET2018 dataset. Similarly, Dataset-2 is constituted using 80% of the samples, i.e., 32000 data samples from the middle east technical university dataset. In this work, Dataset-1 and Dataset-2 are used during the training and validation phases of the model development. In addition, Dataset-3, Dataset-4, Dataset-5, and Dataset-6 are configured to evaluate the final end-to-end performance of the proposed network. The details about these datasets are mentioned in Table 2. The Daataset-3 and Dataset-4 are created using the remaining samples of

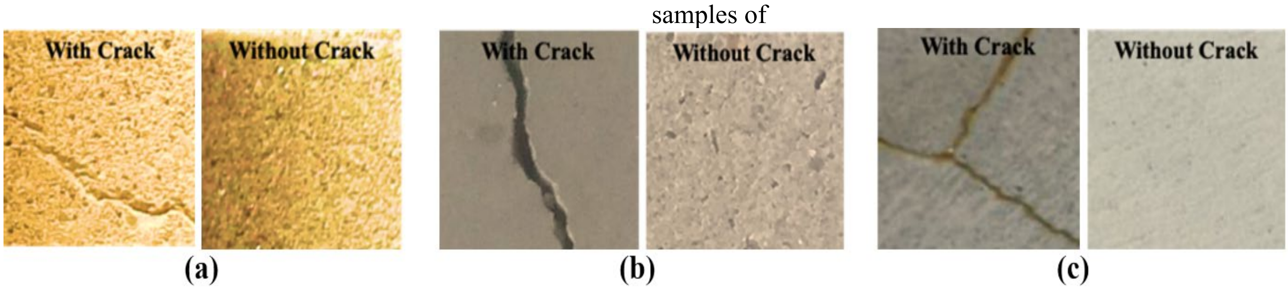


Fig.5 A few Samples from the Three Datasets with Crack and without Crack Categories, (a) Structural Defects Network 2018 Dataset, (b) Middle East Technical University, and (c) Crack-Detection-and-Segmentation Dataset for UAV Inspection.

SDNET2018 and the middle east technical university datasets, respectively, which are not used during the TL and DSSTL phases, whereas Dataset-5 contains all the samples from the crack-detection-and-segmentation dataset. Dataset-6 contains all the samples from the crack-detection-and-segmentation dataset in addition to the remaining samples from the other datasets. Multiple sub-datasets are considered to validate the efficacy of the proposed model and to check its generalization ability under different configurations.

5. Result Analysis and Discussion

To build a robust framework, i.e., STELM with high generalization power for crack detection, this study investigates the application of deep learning techniques such as DSTL and ELM. As illustrated in Fig.3, this work consists of two stages. The first stage is related to exploring a pool of abstract features through conventional TL and DSTL that can be effectively utilized to identify cracks in the surface of concrete structures. In the first stage, we employ the parameters of two ResNets that have already been trained on raw images so that they may be tuned specifically for the surface crack detection task. In the second stage, the extracted pool of distinct abstract features is classified into the respective classes by using an extreme learning machine. To fine-tune the pre-trained networks samples from two different datasets depicting concrete structures with and without cracks are used in this work. Later, the developed model is evaluated with unseen data samples taken from three different datasets to check its accuracy, precision, and generalization capability. The evaluation results indicate that the generalization power of the STELM for detecting cracks in concrete structures is enhanced by the incorporation of DSTL and ELM.

5.1 Abstract features Extraction through Double-Step

In the first step, the ResNet, because of its hierarchical structure and by using nonlinear transformation in the hidden layers, could conveniently explore information from the dataset containing images of cracked structures, hence, updating the parameters of the pre-trained network. As the parameters are updated using images containing cracks in concrete structures, therefore, these updated parameters can be used as approximations of the original dataset, hence, can be used in the completion of the target task. This observation is validated by Fig. 6(a), which contains the distribution of the first two t-SNE feature vectors extracted from the approximations learned by the layers of one of the ResNest models using the conventional TL procedure. It is worth noticing that after fine-tuning through the single-step conventional TL technique, the model was able to explore some non-overlapping distinct features. A non-overlapping distribution of features related to different classes in a classification task is highly desirable as it can significantly improve the classification performance of the end classifier.

In this process, the same network is fine-tuned again on a different dataset containing images of cracks in concrete structures. The idea behind the fine-tuning of the same network for the second time is to provide the network with different information as input, so that it may learn diverse salient information about the target task effectively. This assumption is evident in Fig 6(c), as the distribution of the feature belonging to the two classes is distinct with non-overlapping nature. The non-overlapping distribution of the features significantly enhances the classification performance of the underlying classifier as the overlapping features make it harder for the classifier to distinguish between the samples of different classes if the distribution of the features between the classes is non-distinctive.

In data-driven tasks, it is common that two different datasets collected using different equipment can provide different trends in information, for instance, feature distributions, even if these datasets belong to the same task. Therefore, to complement the information learned during the double-step transfer learning process and to make the proposed method learn as diverse information as possible, in parallel to the double-step transfer network, another pre-trained ResNet model is fine-tuned separately on samples from a different dataset. It will be helpful to would be helpful to gather as much information about the target task as possible, which can later be used to form a hybrid pool of abstract features. The clusters of the abstract features extracted through the second model can be observed in Fig. 6(b). It is evident in the figure that the feature distribution

Table 1. **The Details of the Datasets Used for Transfer Learning Phases.**

Dataset	***Total no. of samples for training and validation***	***Samples with Cracks***	***Samples without Cracks***
Dataset-1	**44800**	**6787**	**38013**
Dataset-2	**32000**	**16000**	**16000**

Table 2. **The Details of the Datasets Used to Evaluate the End-to-End Performance of the Proposed Model.**

Dataset	*Total No of samples used for evaluation*	*Samples with Cracks*	*Samples without Cracks*
Dataset-3	**11200**	**1697**	**9503**
Dataset-4	**8000**	**4000**	**4000**
Dataset-5	**11298**	**12632**	**15677**
Dataset-6	**30489**	**18329**	**29180**

learned through the second model from just using dataset-2 is different from that of Fig. 6(a). So, it can be assumed that combining features learned through the second ResNet model and double-step transfer network forms a diverse pool of abstract features which will provide more vibrant information to the classifier to complete the classification task with high efficacy.

5.2 Result Analysis

After the exploration of distinct abstract features, the next step in STELM is to classify the explored features into their respective classes. For this reason, the concatenated feature pool was provided to an ELM to complete the crack identification process. In traditional ANNs which are generally optimized using gradient descent technique, the generalization power of the network is limited due to the factors like finding the global optima, sensitivity to noisy data, and slow convergence. Therefore, in this study, an ELM is used as a classifier to identify cracks in concrete structures with high generalization ability. The proposed experiment was repeated 20 times with a random selection of samples in train, and test sets using the k-folds cross-validation method to generate stable results. In Fig. 7(a) loss curves for the training and validation phases of the ELM are given. It can be observed from the graph that the error of the network during both the training and validation phases reduced sharply without much oscillation in it. The error of the network was reduced to a minimum of 0.043 percent during the 60thepoch and afterward remained steady. Moreover, Fig. 6(b) shows the training and validation classification accuracy curves of the ELM. It is evident in the graph that the training accuracy of the model initiated above 80% with constant increase and reached the maximum of 99.8 % in the 90th epoch. Furthermore, in Fig. 7(a) the trend of the validation accuracy also shows a similar trend. The validation accuracy of the model started at 0.8407 % with a constant increment with each epoch. In the initial 10 epochs, the validation accuracy has a steep increment reaching 0.9712 % in the 10th epoch, however, after the 10th epoch a steady increase can be seen indicating that the network has learned almost maximum parameters. In the 80th epoch, the model achieved its highest validation accuracy of 99. 3 %, afterward there is no significant change

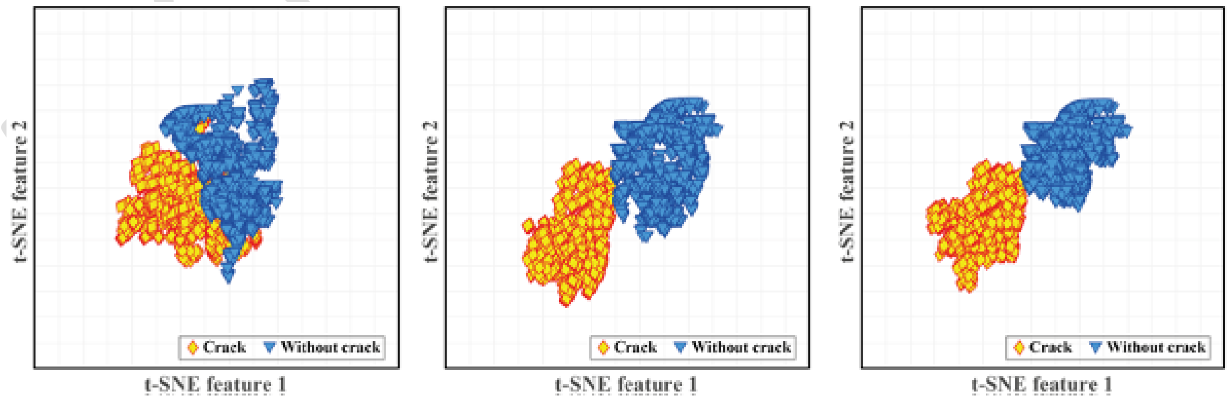
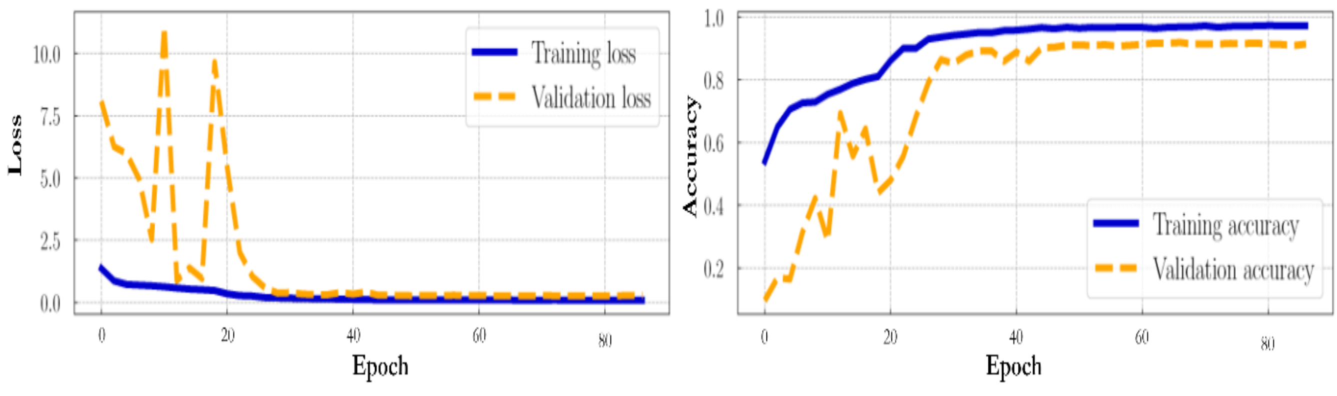


Fig.6 The t-SNE features learned during different stages (a) after the completion of the first step of the transfer learning process, (b) after the completion of the double-step transfer learning process, and (c) Model-2 using dataset-2



(a) Loss curves (b) Accuracy curves

Fig.*7(a)** Loss curves for training and validation phases, ***(b)Accuracy curves for training and validation phases.

in it. The convergence of these error and accuracy curves indicated that the classifier is ready to be tested on unseen data samples. After the completion of the training and validation phases, the performance of the model was evaluated on the

test datasets containing samples that were not used during the training and validation phases.

The average test classification accuracy of the end-to-end model on the four test datasets as described in section 4 is shown in Table 3 along with F1, recall and precision scores. The proposed model achieved PACA of 99.57 %, F1-score, recall, and precision scores of 98.9%, 98.5%, and 99.3%, respectively, when tested on the samples from Dataset-3. Similarly, when evaluated using samples from Dataset-4 it has 99.70 %, 99.6%, 99.3%, and 99.7% of PACA, F1 score, recall and precision values, respectively. Moreover, when tested with samples from Dataset-5 it yielded 99.4% of PACA, 99.1% of F1 score, as well as, 98.9% and 99.4% of recall and precision values, respectively. Furthermore, for Dataset-6 the PACA, F1 score, recall and precession values of the proposed model are 98%, 98%, 97.02%, and 99%, respectively. Out of all the configurations, the proposed model for concrete crack detection has the least performance when tested with Dataset-6. It is due to the fact that Dataset-6 is the most complex dataset as it contained the greatest number of test samples and diverse information because it was constituted by combining samples from three different datasets taken under different configurations. Nevertheless, instead of this much complexity still the proposed model was able to identify the correct category of the samples more than 90% of the time. Based on this performance it is safe to assume that the proposed model can segregate the samples containing cracks from those without cracks with high precision and accuracy even if it is tested with unseen real-time data. It is noteworthy that the test dataset was composed of images randomly selected in Dataset-3, Dataset-4, Dataset-5 and the whole Dataset-6 which were not used during the training phase. This arrangement is helpful in removing data-level biases in the presented experimental results. Moreover, the use of an extreme learning machine as a classifier further ensures the generalization of classification results.

Table 3. The Results for the Test Phase of the Proposed Model (STELM).

Datasets	***Performance indicators (%)***			
	PACA	***F1-Score***	***Recall***	***Precision***
Dataset-3	**99.57**	**98.9**	**98.5**	**99.3**
Dataset-4	**99.7**	**99.6**	**99.3**	**99.7**
Dataset-5	**99.4**	**99.1**	**98.9**	**99.4**
Dataset-6	**98**	**98**	**97.02**	**99**

To further evaluate the performance of the proposed crack identification model, its performance is compared with that of the state-of-the-art studies available on the topic. The comparison results are presented in Fig. 8 where it is evident that the classification performance in terms of average accuracy of the proposed model is greater than the rest of the models. The average classification accuracy of the proposed model is 99.5, followed by ResNet used in [19]for crack detection. The least accurate model is the integrated CNN proposed in [21] for crack detection in concrete structures. Moreover, the precision of the proposed model to detect cracks is at least 0.8% higher than the rest of the models considered for the comparison. The recall value of the proposed model is at least 4.8% higher than other algorithms in this comparison. It is noteworthy that the performance to identify images with crack in the case of the proposed model and ResNet model used in [24] is higher than 99 % but it is 94.3 % in the case of the integrated CNN model proposed in [21]. The performance of the models is mainly affected by the misclassification of images without cracks as images with cracks. The reasons behind this misclassification can be, (1) the misbalance of samples between two classes, (2) unclear appearances of the pixels in the images due to which the classifier could not segregate the images appropriately.

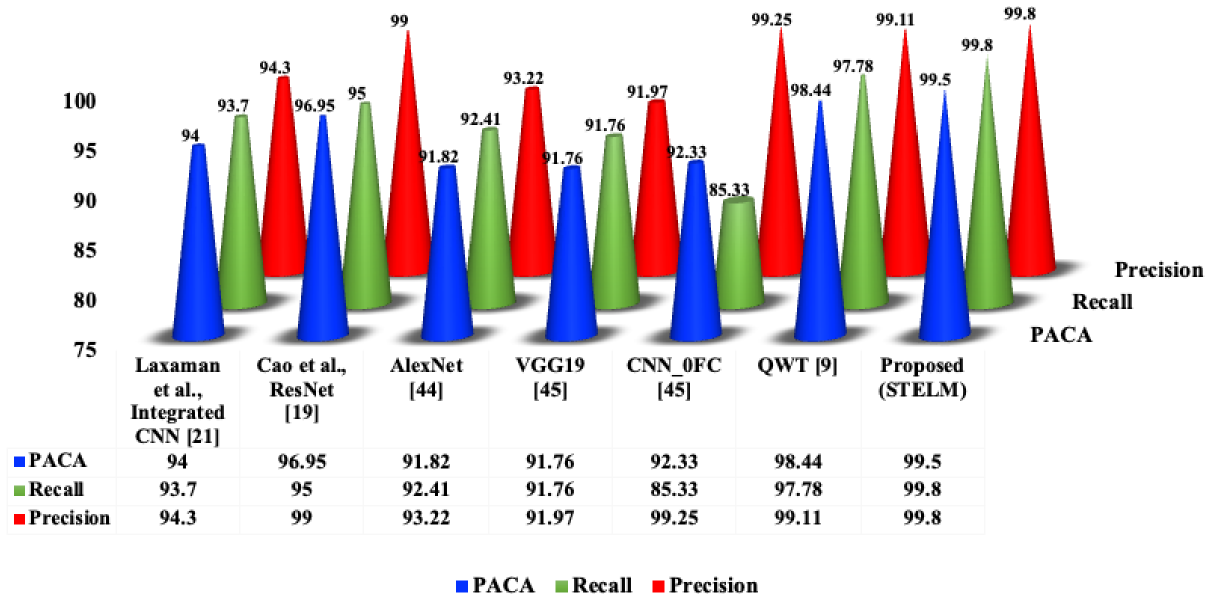


***Fig.*8** The Results of the Comparison of the STELM with Other State-of-the-Art Algorithms.

6. Conclusion

In this paper, a step transfer learning added extreme learning machine, i.e., STELM is proposed to detect cracks in concrete structures. The first step in STELM consisted of the exploration of abstract features suitable for the target task by fine-tuning two different pre-trained ResNets simultaneously using a transfer learning process. A double-step knowledge transfer process was performed on one of the pre-trained ResNet models to extract an abstract feature pool suitable for the target task using two different datasets containing images of cracks in concrete structures. Similarly, another abstract features pool was explored simultaneously through the knowledge transfer process via a different pre-trained Resnet using a different dataset containing images of structures with cracks. The aim was to create a diverse pool of abstract features by concatenating the two feature sets explored from two different datasets through two different models which can provide vibrant information to the classifier to complete the classification task. In the next step of STELM, the pool of concatenated abstract features enriched with salient information was provided to an extreme learning machine to identify cracks with high precision and accuracy. The extreme learning machine is used in this study contrary to most of the approaches present in the literature available for concrete crack detection due to its high generalization power. The efficacy of the proposed crack detection model is validated in the result section through matrixes like accuracy, precision, and recall values. The proposed model was able to acquire 99.5 % accuracy as well as 99.8 % of precision and recall scores which is at least 0.8 % in terms of accuracy and 4.8 % higher in terms of precision and recall than the rest of the models considered for the comparison. It is important to mention that the proposed model misclassified a few of the samples that belonged to that class representing no cracks as images with cracks. This can be due to the unequal number of samples in both the classes and image characteristics, for instance, pixel illumination, and resolution. Nevertheless, the overall crack detection performance of the proposed model is satisfactory and can be relied upon for this purpose.

Acknowledgements

This work was funded by the National Natural Science Foundation of China NSFC62272419, U22A20102, Natural Science Foundation of Zhejiang Province

ZJNSFLZ22F020010 and Zhejiang Normal University Research Fund YS304023947.

References

[1] C. Koch, K. Georgieva, V. Kasireddy, … B. A.-A. E., and undefined 2015, "A review on computer vision based defect detection and condition assessment of concrete and asphalt civil infrastructure," *Elsevier*, Accessed: May 02, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1474034615000208

[2] H. S. Munawar, A. W. A. Hammad, A. Haddad, C. A. P. Soares, and S. T. Waller, "Image-Based Crack Detection Methods: A Review," *Infrastructures 2021, Vol. 6, Page 115*, vol. 6, no. 8, p. 115, Aug. 2021, doi: 10.3390/INFRASTRUCTURES6080115.

[3] L. K. C *et al.*, "Determination of vehicle loads on bridges by acoustic emission and an improved ensemble artificial neural network," *Elsevier*, 2022, doi: 10.1016/j.conbuildmat.2022.129844.

[4] F. Seemab, M. Schmidt, A. Baktheer, M. Classen, and R. Chudoba, "Automated detection of propagating cracks in RC beams without shear reinforcement based on DIC-controlled modeling of damage localization," *Eng Struct*, vol. 286, p. 116118, Jul. 2023, doi: 10.1016/J.ENGSTRUCT.2023.116118.

[5] H. Kim, E. Ahn, M. Shin, S. S.-S. H. Monitoring, and undefined 2019, "Crack and noncrack classification from concrete surface images using machine learning," *journals.sagepub.com*, vol. 18, no. 3, pp. 725–738, May 2019, doi: 10.1177/1475921718768747.

[6] M. Amran, G. Murali, N. Makul, M. Kurpińska, and M. L. Nehdi, "Fire-induced spalling of ultra-high performance concrete: A systematic critical review," *Constr Build Mater*, vol. 373, p. 130869, Apr. 2023, doi: 10.1016/J.CONBUILDMAT.2023.130869.

[7] M. Amran, S. S. Huang, A. M. Onaizi, G. Murali, and H. S. Abdelgader, "Fire spalling behavior of high-strength concrete: A critical review," *Constr Build Mater*, vol. 341, p. 127902, Jul. 2022, doi: 10.1016/J.CONBUILDMAT.2022.127902.

[8] X. Long, S. Zhao, C. Jiang, W. Li, C. L.-E. Fracture, and undefined 2021, "Deep learning-based planar crack damage evaluation using convolutional neural networks," *Elsevier*, Accessed: May 02, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0013794421000758

[9] R. Ahila Priyadharshini, S. Arivazhagan, and M. Arun, "Crack recognition on concrete structures based on machine crafted and hand crafted features," *Expert Syst Appl*, vol. 228, p. 120447, Oct. 2023, doi: 10.1016/J.ESWA.2023.120447.

[10] M. Iraniparast, S. Ranjbar, M. Rahai, and F. Moghadas Nejad, "Surface concrete cracks detection and segmentation using transfer learning and multi-resolution image processing," *Structures*, vol. 54, pp. 386–398, Aug. 2023, doi: 10.1016/J.ISTRUC.2023.05.062.

[11] J. Valença, I. Puente, E. Júlio, H. G.-J.-… and B. Materials, and undefined 2017, "Assessment of cracks on concrete bridges using image processing supported by laser scanning survey," *Elsevier*, Accessed: May 02, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0950061817307456

[12] J. K. Chow *et al.*, "Automated defect inspection of concrete structures," *Autom Constr*, vol. 132, p. 103959, Dec. 2021, doi: 10.1016/J.AUTCON.2021.103959.

[13] F. Thériault, M. Noël, and L. Sanchez, "Simplified approach for quantitative inspections of concrete structures using digital image correlation," *Eng Struct*, vol. 252, p. 113725, Feb. 2022, doi: 10.1016/J.ENGSTRUCT.2021.113725.

[14] M. C. Naoum, N. A. Papadopoulos, M. E. Voutetaki, and C. E. Chalioris, "Structural Health Monitoring of Fiber-Reinforced Concrete Prisms with Polyolefin Macro-Fibers Using a Piezoelectric Materials Network under Various Load-Induced Stress," *Buildings*, vol. 13, no. 10, p. 2465, 2023.

[15] M. P. Tinoco and F. de Andrade Silva, "On the mechanical behavior of hybrid fiber reinforced strain hardening cementitious composites subjected to monotonic and cyclic loading," *Journal of Materials Research and Technology*, vol. 11, pp. 754–768, 2021.

[16] D. G. Aggelis, A. C. Mpalaskas, and T. E. Matikas, "Acoustic monitoring for the evaluation of concrete structures and materials," in *Acoustic Emission and Related Non-Destructive Evaluation Techniques in the Fracture Mechanics of Concrete*, Elsevier, 2015, pp. 269–286.

[17] N. Metni and T. Hamel, "A UAV for bridge inspection: Visual servoing control law with orientation limits," *Autom Constr*, vol. 17, no. 1, pp.

3–10, Nov. 2007, doi: 10.1016/J.AUTCON.2006.12.010.

[18] S. Teng, Z. Liu, G. Chen, and L. Cheng, "Concrete Crack Detection Based on Well-Known Feature Extractor Model and the YOLO_v2 Network," *Applied Sciences 2021, Vol. 11, Page 813*, vol. 11, no. 2, p. 813, Jan. 2021, doi: 10.3390/APP11020813.

[19] C. D.-A. in Construction and undefined 2019, "Autonomous concrete crack detection using deep fully convolutional neural network," *Elsevier*, Accessed: Jun. 01, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0926580518306745

[20] I. Abdel-Qader, O. Abudayyeh, and M. E. Kelly, "Analysis of Edge-Detection Techniques for Crack Identification in Bridges," *Journal of Computing in Civil Engineering*, vol. 17, no. 4, pp. 255–263, Oct. 2003, doi: 10.1061/(ASCE)0887-3801(2003)17:4(255).

[21] K. Laxman, N. Tabassum, L. Ai, … C. C.-C. and B., and undefined 2023, "Automated crack detection and crack depth prediction for reinforced concrete structures using deep learning," *Elsevier*, Accessed: Jun. 01, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0950061823004208

[22] T. Yamaguchi and S. Hashimoto, "Improved percolation-based method for crack detection in concrete surface images," in *2008 19th International Conference on Pattern Recognition*, IEEE, 2008, pp. 1–4.

[23] H. Kim, J. Lee, E. Ahn, S. Cho, M. Shin, and S.-H. Sim, "Concrete crack identification using a UAV incorporating hybrid image processing," *Sensors*, vol. 17, no. 9, p. 2052, 2017.

[24] J. Shu, C. Zhang, X. Chen, and Y. Niu, "Model-informed deep learning strategy with vision measurement for damage identification of truss structures," *Mech Syst Signal Process*, vol. 196, p. 110327, Aug. 2023, doi: 10.1016/J.YMSSP.2023.110327.

[25] L. Sun, Z. Shang, Y. Xia, S. Bhowmick, and S. Nagarajaiah, "Review of Bridge Structural Health Monitoring Aided by Big Data and Artificial Intelligence: From Condition Assessment to Damage Detection," *Journal of Structural Engineering*, vol. 146, no. 5, p. 04020073, Mar. 2020, doi: 10.1061/(ASCE)ST.1943-541X.0002535.

[26] J. Shu, W. Li, C. Zhang, Y. Gao, Y. Xiang, and L. Ma, "Point cloud-based dimensional quality assessment of precast concrete components using deep learning," *Journal of Building Engineering*, vol. 70, p. 106391, Jul. 2023, doi: 10.1016/J.JOBE.2023.106391.

[27] J. Shu, W. Ding, J. Zhang, F. Lin, and Y. Duan, "Continual-learning-based framework for structural damage recognition," *Struct Control Health Monit*, vol. 29, no. 11, p. e3093, Nov. 2022, doi: 10.1002/STC.3093.

[28] J. Zhang, S. Qian, and C. Tan, "Automated bridge surface crack detection and segmentation using computer vision-based deep learning model," *Eng Appl Artif Intell*, vol. 115, p. 105225, Oct. 2022, doi: 10.1016/J.ENGAPPAI.2022.105225.

[29] H. Zhang, Z. Qian, Y. Tan, Y. Xie, and M. Li, "Investigation of pavement crack detection based on deep learning method using weakly supervised instance segmentation framework," *Constr Build Mater*, vol. 358, p. 129117, Dec. 2022, doi: 10.1016/J.CONBUILDMAT.2022.129117.

[30] M. Sohaib and J. M. Kim, "Higher order spectral analysis of vibration signals and convolutional neural network for the fault diagnosis of an induction motor bearings," in *Advances in Intelligent Systems and Computing*, 2019. doi: 10.1007/978-3-030-03302-6_1.

[31] M. Sohaib and J.-M. Kim, "Fault diagnosis of rotary machine bearings under inconsistent working conditions," *IEEE Trans Instrum Meas*, vol. 69, no. 6, pp. 3334–3347, 2019.

[32] L. Chen *et al.*, "Convolutional neural networks (CNNs)-based multi-category damage detection and recognition of high-speed rail (HSR) reinforced concrete (RC) bridges using test images," *Eng Struct*, vol. 276, p. 115306, Feb. 2023, doi: 10.1016/J.ENGSTRUCT.2022.115306.

[33] Z. Liu *et al.*, "Automatic pixel-level detection of vertical cracks in asphalt pavement based on GPR investigation and improved mask R-CNN," *Autom Constr*, vol. 146, p. 104689, Feb. 2023, doi: 10.1016/J.AUTCON.2022.104689.

[34] P. Kumar, A. Sharma, and S. R. Kota, "Automatic Multiclass Instance Segmentation of Concrete Damage Using Deep Learning Model," *IEEE Access*, vol. 9, pp. 90330–90345, 2021, doi: 10.1109/ACCESS.2021.3090961.

[35] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," *3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings*, Sep. 2014, Accessed: Jun. 01, 2023. [Online]. Available: https://arxiv.org/abs/1409.1556v6

[36] K. He, J. S.-P. of the I. conference on computer, and undefined 2015, "Convolutional neural networks at constrained time cost," *cv-foundation.org*, Accessed: Jun. 01, 2023. [Online]. Available: https://www.cv-foundation.org/openaccess/content_cvpr_2015/html/He_Convolutional_Neural_Networks_2015_CVPR_paper.html

[37] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

[38] J. A. Vásquez-Coronel, M. Mora, and K. Vilches, "A Review of multilayer extreme learning machine neural networks," *Artif Intell Rev*, 2023, doi: 10.1007/S10462-023-10478-4.

[39] "What Is Transfer Learning? [Examples & Newbie-Friendly Guide]." Accessed: May 02, 2023. [Online]. Available: https://www.v7labs.com/blog/transfer-learning-guide

[40] "What Is Transfer Learning? A Guide for Deep Learning | Built In." Accessed: May 02, 2023. [Online]. Available: https://builtin.com/data-science/transfer-learning

[41] M. Maguire, S. Dorafshan, and R. J. Thomas, "SDNET2018: A concrete crack image dataset for machine learning applications," *Browse all Datasets*, May 2018, doi: https://doi.org/10.15142/T3TD19.

[42] "Concrete Crack Images for Classification | Kaggle." Accessed: Jun. 01, 2023. [Online]. Available: https://www.kaggle.com/datasets/arnavr10880/concrete-crack-images-for-classification

[43] "GitHub - KangchengLiu/Crack-Detection-and-Segmentation-Dataset-for-UAV-Inspection: :fire: Crack-Detection-and-Segmentation-Dataset-for-UAV-Inspection." Accessed: Jan. 12, 2024. [Online]. Available: https://github.com/KangchengLiu/Crack-Detection-and-Segmentation-Dataset-for-UAV-Inspection?tab=readme-ov-file.

[44] A. Arbaoui, A. Ouahabi, S. Jacques, M. H.- Electronics, and undefined 2021, "Concrete cracks detection and monitoring using deep learning-based multiresolution analysis," mdpi.com, 2021, doi: 10.3390/electronics10151772.

[45] M. Zeeshan, S. Adnan, … W. A.-P. J. of, and undefined 2021, "Structural Crack Detection and Classification using Deep Convolutional Neural Network," sites2.uol.edu.pk, Accessed: Jun. 12, 2023. [Online]. Available: https://sites2.uol.edu.pk/journals/pakjet/article/view/1547.

[46] I. Wijaya, … A. D.-… on A. in, and undefined 2020, "Classification of Building Cracks Image Using the Convolutional Neural Network Method," ieeexplore.ieee.org, Accessed: Jun. 12, 2023. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9276962/.