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Comparative Study and Analysis of Deep Learning Models for Concrete Bridge Crack Detection

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***Abstract*: Infrastructure for transportation relies heavily on concrete bridges, therefore maintaining their health is essential for everyone's safety. A comparison of deep-learning algorithms for spotting cracks in concrete bridges is presented in this work. The proposed models include Convolutional Neural Network (CNN), Convolutional Recurrent Neural Network (CRNN), You Only Look Once (YOLO) versions YOLOv5, YOLOv7, YOLOv8, and Residual Networks (ResNet) leverage cutting-edge deep learning architectures and feature engineering techniques, enabling more precise crack detection in concrete bridge structures. To boost model generalization and the capacity to spot cracks in a variety of real-world scenarios, various data augmentation techniques, such as Gaussian blur, mix-up, random rotation, center crop, random crop, Gaussian noise, random blocks, central region, and smart padding, were also included. The studies utilized cracked and uncracked concrete bridge surface photos from the open-source SDNET dataset. The accuracy, precision, recall, and F1 score of each model are evaluated. YOLOv8 has the highest accuracy of 95%, whereas CNN and YOLOv5 showed poor performance.**

Keywords: CNN, CRNN, YOLOv5, YOLOv7, YOLOv8, ResNet, deep learning, crack detection, bridge cracks

I. Introduction

Concrete bridges are essential parts of the transportation infrastructure because they make it easier to carry people and carry products across different geographical areas. However, as time passes, these bridges experience normal wear and tear, which causes fractures in the concrete construction. Early detection and repair of these cracks are essential for maintaining the bridge's structural integrity and safety. It is a difficult process that frequently depends on visual examinations carried out by qualified staff [1]. This manual approach is time-consuming, labor-intensive, and prone to human mistakes, which emphasizes the requirement for automated solutions that can correctly and effectively identify fractures [2].

Advanced technologies based on deep learning algorithms have emerged as viable alternatives to overcome these constraints and improve the effectiveness and accuracy of crack detection [3, 4]. It has shown astounding capability at interpreting complicated data and producing accurate estimations. It has created new opportunities for various applications, including computer vision works, because of its capacity to learn pertinent characteristics from raw data automatically.

The ability of deep learning algorithms to scan massive volumes of pictures and extract subtle patterns associated with fractures might greatly help concrete bridge crack detection. In other words, these techniques can identify even subtle cracks by harnessing the power of large datasets and complex neural networks that human inspectors may miss. Several research studies have investigated deep learning applications for concrete structure crack detection, like Convolutional Neural Networks (CNNs), Residual Neural Networks (ResNet), to address the challenges of detecting and segmenting minute cracks in concrete surfaces. These algorithms have outperformed more conventional image processing techniques, demonstrating the potential of deep learning to revolutionize crack identification in concrete bridges.

It motivates us to study the existing deep learning techniques. Additionally, perform a comparative analysis of deep learning models: CNN [5, 6], Convolutional Recurrent Neural Networks (CRNNs) [1], various versions of You Only Load Once (YOLO) [7, 8, 9], and ResNet [10]. The objective is to examine the effects of data augmentation approaches for model accuracy and the efficacy of these models in identifying cracks in concrete surfaces. The main contribution of the work is as follows:

- Investigate existing deep-learning approaches for crack detection in concrete bridges.
- Propose deep-learning algorithms tailored specifically for concrete bridge crack detection using data augmentation techniques.
- Evaluate the accuracy of the proposed algorithm on the SDNET concrete bridge crack dataset.

The paper’s organization is as follows: Section 2 discusses the existing literature, and the proposed algorithms are presented in Section 3. Section 4 presents the data augmentation techniques used, and the experimental setup is presented in Section 5. Section 6 analyzes the results in detail, with the conclusion in Section 7.

II. Related Work

Several studies have investigated deep learning techniques for concrete bridge crack detection. This paper mainly discusses the existing works on four deep learning algorithms: CNN, ResNet, YOLO versions, and other algorithms applied for bridge crack detection:

A. Convolutional Neural Networks

A deep hierarchical convolutional neural network (CNN) was developed to detect pixel-wise cracks using images retrieved from the Internet. To improve the prediction results, guided filtering and conditional random fields were applied in a densely supervised network layer [5]. Dung and Anh devised an autonomous system for identifying concrete fractures employing a deep full CNN that achieved 90% average precision for 500 annotated 227*227 pixel images [6].

An annotated public benchmark images included 6900+ photos of cracked and uncracked concrete culverts and bridges. The classification of cracked and uncracked images was done using three cutting-edge DCNNs, and the highest accuracy tested was 95.89% [12].

CNN-based crack detection to identify fractures in photographs of concrete bridges precisely and for automating quantitative assessments of recognized fractures, Bilateral-Graying-Contrast (BGC), a hybrid image processing technique, was developed. The measurement error of the suggested crack measuring system is significantly reduced to 9.86%, making it a trustworthy tool for analyzing concrete bridge pictures [13].

Customization of CNN with VGG-16, which outperforms the other approaches in localization, classification, and computational cost on a short and varied data sample. Training data amount and sample variability significantly impact the model's performance. All models showed impressive results on small data. On the other hand, when training data quantity and variety were increased, generalization efficiency decreased, resulting in over-fitting. [14].

A flexible crack recognition approach was proposed that utilized the sliding window technique to compile a dataset of bridge fractures. The suggested context encoder network includes RRCNN, DAC, and RMP to collect low-level characteristics while keeping relevant cracked details from the crack picture.

B. Residual Networks (ResNet)

ResNet models also showed promising results like a ResNeXt+PP model was developed to find cracks effectively. The potential crack zones were extracted using the picture binarization method. The trained, improved ResNeXt+PP model was superior to multiple crack identification methods [15].

Another ResNet-like technique named MR-CrackNet was developed to identify and localize various-sized infrastructure fractures. MR-CrackNet beat baseline models to extract major crack characteristics and achieved high accuracy. A crack dataset of 2,532 pictures was used to train and test the model [16].

Adhikari et al. [17] created an integrated model for numerically representing faults based on digital image processing. The crack quantification model calculates crack lengths according to the circumference of a crack's skeleton. The Fourier Transform of digital pictures is used in the change detection model, eliminating the need to register images.

C. You Only Look Once (YOLO)

The YOLO_v2 network with the ‘resnet18’ feature extractor model achieved the best crack detection results regarding precision and computational cost. Different YOLO_v2 feature extractor networks like training epoch, feature extraction layer, and testing image size impact the detection results [18]. To identify bridge surface fractures in real time, an enhanced YOLO v3 algorithm was developed. To minimize the number of network parameters and enhance precision, MobileNets and convolutional block attention modules (CBAM) are utilized [19].

YOLOv4 is an effective method for detecting apparent damage to concrete structure bridges. To develop a model for detecting fractures on bridge surfaces, a YOLOv4 deep learning model was utilized. The model was 92% accurate, with measured width as accurate as 0.22 mm. The suggested method allowed for bridge assessments and the collection of quantitative and qualitative information [20].

An improved YOLOv4 model was developed to detect concrete surface cracks, which achieved 94.09% mAP with 8.04 M and 0.64 GMacs. Adopting the symmetry principle, separable convolution, and enhancing the SPP and PANet modules helped enhance the model. The model's size and computation cost were considerably lowered, allowing it to identify concrete surface fractures in real time [21]. Lightweight vision models and YOLOv4 were used to propose an automated bridge crack detection method. The method achieved 92.5% accuracy, 91.3% precision, 94.2% recall, and 92.7% F1 score on the SDNET dataset [22].

The light-weighted crack detection model's main foundation has been YOLOv5s. Sun et al. [23] improved the YOLOv5 detector by adding a convolutional block attention module, a decoupled prediction head, and a focused loss function. They obtained 90.3% mAP50 and 72.8% mAP75, higher than the original YOLOv5.

Yu et al. [24] proposed a deep learning-assisted image processing approach that employed a ratio filter and mask filter to remove the speckle linear noises and handwritten marks. According to experimental data, the suggested approach accurately detects, quantifies, and visualizes cracks bigger than 0.15 mm.

D. Other Deep Learning Algorithms

Prasanna et al. [25] developed the STRUM (spatially tuned robust multi-feature) classifier that eliminated the need to modify threshold values manually. The technique employed powerful curve fitting to localize probable crack locations even in noise spatially. The classification results indicated a peak STRUM classifier performance of 95%.

For concrete crack detection, U-Net is more effective and resilient than DCNN. The u-Net-based concrete crack detection technique outperformed FCNs in terms of accuracy with a smaller training set [26]. Pan et al. (2020) introduced a spatial-channel hierarchical deep learning network for pixel-level automatic crack identification that is resilient to noise and can identify and localize cracks correctly [27].

Wang and Cha [28] suggested a deep auto-encoder and one class support vector machine-based unsupervised deep-learning technique for defect identification. The results demonstrated the ability to identify fractures without labeled training data. Qiao et al. [29] proposed deep CNN with the expectation of a maximum attention module (EMA-DenseNet).

Branikas et al. proposed a novel data augmentation method using cycle generative adversarial networks to improve segmentation accuracy showing its effectiveness in enhancing crack detection performance [30]. MSCNet, a framework containing a texture improvement technique and feature aggregation for crack identification, was proposed by Lu et al. [31]. Dorafshan et al. [32] explored deep-learning NN for sUAS-assisted structural inspections, including crack detection. The evaluation metrics varied across the neural network models but demonstrated high accuracy, precision, recall, and F1 scores for crack detection.

A Naive Bayes fully convolutional network (NB-FCN) with a multi-layer features extraction method were proposed to automate cracks segmentation and noise. The results were validated on 7200 images of bridge structures gathered from 20 in-service bridges under varied conditions. The results outperformed other recent algorithms for accuracy, computational cost, and error rates [33]. The detection of fractures in concrete roadways using a deep learning-based object detection algorithm under diverse shooting, weather, and illumination circumstances was performed [34]. The number of trials observed on a sunny day remains constant. On a dark and foggy day, it drops by 85% between 7:00–8:00 pm, 25% at 6:00–7:00 pm, and 50% between sunset and moonlight, but not at 5:00–6:00 pm. The suggested approach efficiently finds fractures in concrete roadways under various shooting, weather, and lighting situations. The Fourier Transform of digital pictures serves as the foundation for the change detection paradigm, eliminating the necessity for image registration [35][36]. The deep learning methods for fracture detection in concrete bridges are listed in Table 1.

Table 1. Comparison of various deep learning algorithms used to detect concrete bridge cracks

Ref No.	Author (Year)	Algorithms Used	Performance measures	Datasets
[6]	Dung and Anh (2019)	Fully Convolutional Network (FCN)	Average precision	Annotated 500 227 × 227-pixeled crack-labeled images
[12]	Zoubir et al. (2021)	Deep CNN	Accuracy	SDNET2018
[14]	Ali et al. (2021)	CNN+VGG-16	Accuracy, precision, recall, and F-score	Public datasets
[16]	Nayyeri and Zhou (2021)	ResNet-like approach called MR-CrackNet	accuracy	2,532 images
[18]	Teng et al. (2021)	YOLOv2	Precision and computational cost	990 RGB crack images of a concrete bridge
[20]	Kao et al. (2023)	YOLOv4	Accuracy, width measurement	Photographs of bridge surfaces cracks captured with UAV-mounted camera
[21]	Yao et al. (2021)	YOLOv4	Mean average precision (mAP)	10,000 images
[23]	Sun et al. (2022)	YOLOv5	Mean average precision (mAP)	Open bridge surface defect dataset
[25]	Prasanna et al. (2016)	STRUM (spatially tuned robust multi-feature) classifier	Crack detection, accuracy, crack density map	Real bridge data
[33]	Li et al. (2020)	Naive Bayes -fully convolutional network (NB-FCN)	Recognition accuracy, computation time, and error rates	7200 images of 10 bridges
[34]	Hacıefendioğlu and Başağa (2022)	Faster R-CNN	Number of cracks detected	323 images

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III. Proposed Algorithms

This section explains the working of the proposed deep learning models that could effectively detect cracks in concrete bridges as follows. Furthermore, the crack detection capabilities of the models were enhanced by incorporating pre-processing techniques and optimizing the hyper-parameters of the models to provide reliable solutions for concrete bridge maintenance and damage inspection.

A. Convolutional Neural Network

The CNN model follows a typical pattern. It starts with a sequence of Conv2D layers, each followed by an activation function and a pooling layer. This pattern helps the model learn hierarchical representations of the input images. After the convolutional layers, the feature maps are flattened and passed through fully connected (FC) layers, each followed by an activation function. The final FC layer produces the output of the model.

B. Convolutional Recurrent Neural Network (CRNN)

The CRNN model combines convolutional layers with recurrent layers. It begins with Conv2D layers followed by activation and pooling layers, like the CNN model. The output of the pooling layer is then reshaped to fit the input of LSTM (Long Short-Term Memory) layers. The LSTM layers are especially helpful for jobs requiring sequential data because they capture temporal relationships in the data. The output is then generated by a fully linked layer with an activation function.

C. Residual Network (ResNet)

The ResNet model design uses residual connections to solve the vanishing gradients in deep neural networks. It begins with a substantial 7x7 Convolutional layer and then moves on to max pooling. The model comprises convolutional layers with shortcut connections that omit one or more layers. This makes it possible for information to be transmitted directly and makes it easier to train deeper networks. The output is produced by fully connected layers in the final layer.

D. You Only Look Once

Three of the YOLO variants, out of the many available, are used in the proposed work.

1) YOLOv5

The architecture of the YOLOv5 model is built around several bottleneck components. Each block comprises many Conv3x3 layers, which are then downsampled. Every block has more filters, which enables the model to record more intricate details. Additional convolutional layers are added after the bottleneck blocks, gradually reducing the feature maps' spatial dimensions. To create the output, the final layers include a 1x1 convolution, a 3x3 convolution, and a 1x1 convolution.

2) YOLOv7

Like YOLOv5, the YOLOv7 model design has a set of bottleneck blocks and down-sampling processes. The model's foundation comprises a 3x3 convolutional layer and many bottleneck blocks. Conv3x3 layers compose each bottleneck block, progressively increasing the number of filters. These building components are intended to collect characteristics of various sizes and improve object detection. The spatial dimensions of the feature maps are minimized by finishing the model with some extra convolutional layers. The result is then produced by applying a 1x1 convolution, a 3x3 convolution, and a 1x1 convolution.

3) YOLOv8

The YOLOv8 model uses a deep and broad network to identify objects accurately, even with microscopic fractures. Its architecture is based on a sequence of bottleneck blocks with increasing filter sizes. Each block comprises many down-sampled Conv3x3 layers and additional filters to capture more intricate details at various sizes. Additional convolutional layers are added after the bottleneck blocks to reduce the feature maps' spatial dimensions gradually. To create the output, the final layers include a 1x1 convolution, a 3x3 convolution, and a 1x1 convolution.

IV. Data Augmentation Techniques

Several pre-processing approaches and feature engineering methods were used to improve crack identification skills and manage various changes in the pictures of the models [17]. Concatenation-based augmentation was used to augment the dataset by combining images from different sources. The grayscale conversion was applied to simplify the image representation and reduce computational complexity. Mixup generated synthetic samples by blending images and their corresponding labels, facilitating improved generalization. Random rotation was used to rotate the photos by an arbitrary angle to simulate different orientations of the cracks. Center crop and random crop were used to randomly crop the images to simulate different scales of the cracks. Gaussian noise was used to add random noise to the photos, while random blocks were used to randomly remove parts of the image. Finally, central region and smart padding were used to preserve the image’s central area and pad the images with zeros to maintain the image size.

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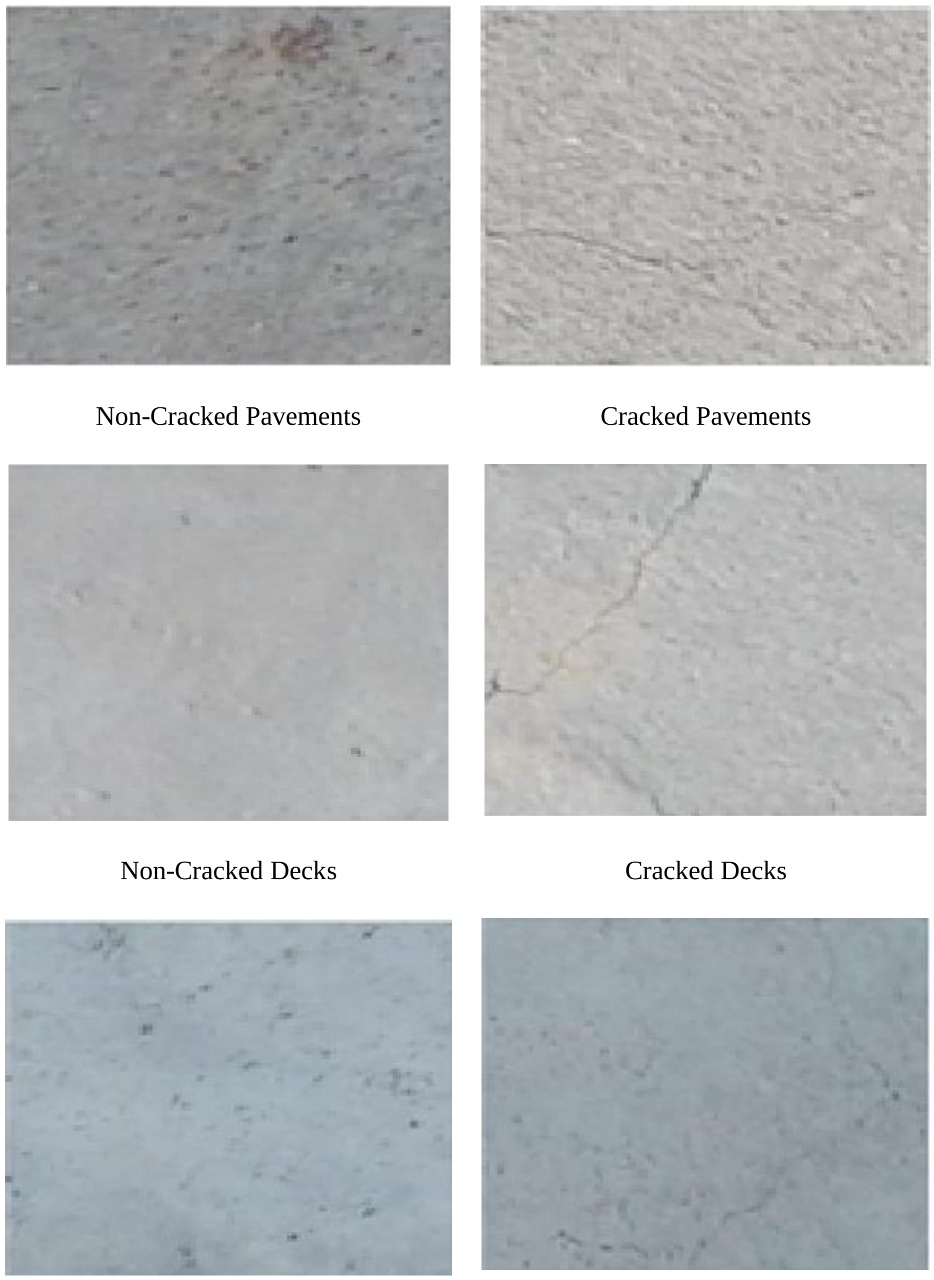

Figure 1. Cracked and Non–Cracked Image samples.

V. Experimental Setup

The experiment is performed on a laptop with Intel(R) Core (TM) i7-11370H CPU 3.30 GHz with 16.0 GB RAM. The Python shell version 3.10.11 is utilized to build the application program. The SDNET dataset was the primary dataset for training and testing the models [16]. The dataset contains 56,634 images of cracked and non-cracked concrete bridge surfaces. The photos are divided into decks, pavements, and walls. Each category contains two subdirectories: cracked and non-cracked. The images have a resolution of 2272 x 1704 pixels and are in JPEG format. Figure 1 shows the sample images. Initially, the SDNET dataset was pre-processed using Gaussian blur to remove the noise present in the images. Next, feature engineering techniques like mix-up, random rotation, center crop, random crop, Gaussian noise, random blocks, central region, and smart padding were applied to the pre-processed dataset. This was done to improve the model's accuracy and make it more robust to different crack patterns.

A batch size of 32 was set during the training process, and the models were trained for 50 epochs. The learning rate was 0.001 for CNN, CRNN, ResNet, YOLOv7, YOLOv5, and YOLOv8. The Adam optimizer, known for its efficiency in handling large-scale datasets, was employed. Binary cross entropy was used as the loss function for all models, and the ReLU activation function was utilized throughout the network architecture. Appropriate evaluation metrics such as accuracy, precision, recall, and F1-score were employed to evaluate the models' performance.

VI. Results and Analysis

This section presents the results obtained from the proposed algorithms; their metrics values are shown in Table 1.

Table 2 Comparative analysis of models using evaluation metrics

Evaluation Metrics/ Models	Accuracy	Precision	Recall	F1 Score
CNN	85%	97.29%	95.81%	95.79%
CRNN	90%	95.97%	96.34%	96.16%
ResNet	90%	97.27%	97.63%	97.45%
YOLOv5	80%	97.29%	97.06%	97.17%
YOLOv7	93%	92%	94%	93%
YOLOv8	**95%**	**97.97%**	**98.05%**	**98.05%**

It is observed from the table that YOLOv8 emerged as the most effective model, achieving an accuracy of 95% and outperforming other models in precision, recall, and F1 score. YOLOv7 followed with an accuracy of 93%, while CRNN and ResNet achieved accuracies of 90%. CNN had the lowest accuracy of 85%, indicating its lesser effectiveness for crack detection (see Figure 2).

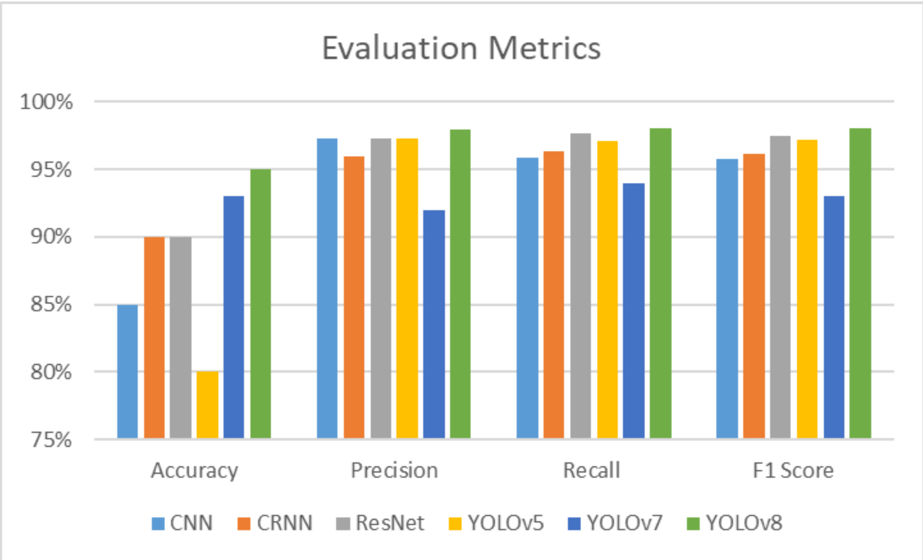

Figure 2. Model Comparison for the Evaluation Metrics

The lower accuracy of the CNN model compared to the other models for crack detection can be attributed to its architectural limitations. CNNs are primarily designed for image classification tasks. They may struggle with detecting small or subtle features like cracks in concrete bridges because of fewer layers and less capacity to obtain complex spatial patterns and temporal dependencies. Conversely, models like YOLOv5, YOLOv7, and YOLOv8, as well as CRNN and ResNet, have better architectures to capture finer features and relationships. In other words, these models are more accurate in identifying fractures in concrete bridges because of their superior design and architecture compared to CNN.

More information about the effectiveness of crack detection models may be gleaned from the assessment measures they utilize, such as accuracy, recall, and F1 score. The F1 score strikes an equilibrium between recall and precision by measuring the accuracy of positive predictions (precision) and the capacity to recognize all positive occurrences (recall). The F1 score (98.05%), recall (98.05%), and accuracy (97.97%) of YOLOv8 were the highest, demonstrating its outstanding ability to recognize cracks. ResNet also worked well, and CRNN and YOLOv5 produced acceptable outcomes. The CNN model performed considerably poorly in damage detection, as seen by its lowest accuracy, recall, and F1 scores.

Overall, YOLOv8 outperformed YOLOv5 and ResNet in correctly categorizing cracked and non-cracked photos.

VII. Conclusions

In this study, we reviewed the existing literature illustrating how deep learning models may identify cracks in concrete bridges, offering a practical and helpful approach to maintaining and safeguarding bridges. We also proposed the following deep learning models: YOLOv5, YOLOv7, YOLOv8, CRNN, CNN, and ResNet, and improved their performance using data augmentation techniques. The results are validated using the SDNET dataset and compared with their accuracy, precision, recall, and F1 scores. It is observed that YOLOv8 provided the highest accuracy rate of 95%. To further increase the models' accuracy, future work will optimize the hyperparameters and incorporate transfer learning. The study may also be expanded by validating the models' performance in real-world circumstances using a more extensive and varied dataset.

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