Research Article

Identification of Civil Infrastructure Damage Using Ensemble Transfer Learning Model

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This article uses cutting-edge deep learning technology to identify structural damage from images for a civil engineering application. The public infrastructures of the country are generally inspected physically by a visual evaluation by qualified inspectors. However, manual inspections are pretty time-consuming and often require too much labor. The number of experts capable of evaluating such structural damage is inadequate. As a result, computer vision-based techniques for automatic damage detection have been developed. This paper’s civil infrastructure damages are classified into four damages of roads common in Indian highways and the concrete deterioration in the bridges. The convolutional neural network has become a standard tool for organizing and recognizing images. In this paper, an ensemble of three CNN models is proposed, and two are transfer learning-based models. The proposed ensemble transfer learning model provided a validation accuracy of 87.1%.

1. Introduction

Bridges, highways, lifeline networks, and houses are only a few examples of critical infrastructure that was constructed decades ago and is no longer fit for purpose. As per the American Society of Civil Engineers’ 2017 Infrastructure Report Card, the USA has over 56,000 operationally defective bridges that would cost an additional 123 billion dollars to patch [1]. Data collected by evaluation and assessment processes is often used to determine the state of structural design. Conventional methods for monitoring the effects of structural design comprise routine examination by qualified inspectors along with specific decision-making criteria. Such inspections, on the other hand, can be time-consuming, labor-intensive, costly, and hazardous [2]. Monitoring can be used to get a quantitative understanding of a structure’s current condition by measuring the physical quantities like excitations, pressures, and lateral displacement; such methods allow for seamless concrete structures surveillance in real time, with the expectation of achieving...
sential infrastructure such as bridges and roads [1]. Although these approaches have been shown to yield accurate findings, they usually have low visual acuity or require massive sensing devices to be installed. Another problem is that when the sensors are integrated, access to them is often limited, causing device management to be difficult. Contact sensor installation is challenging and time-consuming when periodic monitoring is required [4]. To advance and understand the benefits of automated civil infrastructure condition assessment, improved inspection and monitoring approaches with less human interference, lower cost, and higher spatial resolution must be developed and tested. Government agencies expend substantial amounts of money conducting routine inspections of essential infrastructure such as bridges and roads [1].

Furthermore, systemic response records and photographs as data media are becoming increasingly important in today's data explosion, especially in deep learning (DL) applications in computer vision, which have made significant progress in recent years. Furthermore, the application of machine learning and deep learning aims to make computers perform labor-intensive repetitive tasks while also learning from previous experiences [2]. In recent days, vision-based structural health monitoring is used to identify structural damage detection, which heavily relies on the experience of the human to do a visual inspection. In this proposed work, the civil infrastructure damages considered are concrete deterioration in the bridges, road cracks, road potholes, road rutting, and road lines [3]. First, the concrete deterioration in the bridges is considered due to a reduction in the lifespan of the reinforcement steel. Bridge collapses are equivalent to plane crashes and natural disasters resulting in injury, loss of life, and property damage [4]. Common bridge damages are corrosion, leaching, cracks, and scaling of the concrete surface to identify conditions; the bridge structures are exposed to a series of destructive tests including cutting, sewing, and taking core samples. It helps in analyzing the core profile and testing the bridges. However, coring increases the risk of damaging an already damaged structure due to the removal of concrete by cutting, sewing, and core sample. Destructive testing methods are not ideal for locating the bridge structures' damage comprising a larger area [5].

Secondly, the road network in India extremely covers a larger area to connect various places through roadways. However, the maintenance of the roads is so poor. As roads contribute indirectly to the country’s economic development, the roads must be well laid out and solid. India being a developing country, the need for well-maintained civil infrastructure is growing. Being the largest country with the highest population, this problem is yet to be addressed in India. Therefore, numerous solutions for automated road damage inspection, including 3D methods, vibration-based techniques, and vision-based techniques, were provided by researchers [6]. The vibration detection techniques are limited to the contact road section. While thermal imaging approaches provide detailed information on road damages, there is a need to close the door. The 3D hologram images are generated using quaternion Fresnel transform of civil infrastructure to analyze its condition [7].

In the meantime, image processing techniques are cost-effective. However, it can be hampered by a lack of accuracy. Road damages are one of the root causes of road accidents and need to be maintained appropriately to avoid dangerous accidents. A pothole is caused due to the damage in the asphalt sheet internally, which affects the surface of the pavement [8]. Owing to the poor soil quality, extreme temperature fluctuations create such potholes. Hair, edge joint, lane joint, widening, edge, perception, evaporation, alligator, and erosion are the nine distinct types of cracks found in the road's superficial layer. The cracks in the roads may lead to delay in travel time and increased costs due to excessive fuel consumption and vehicle maintenance [9]. Early detection of such cracks and other damages is essential to avoid the severe problems caused due to pavement failures. Deep convolutional neural networks (CNNs) are useful in a variety of applications such as computer vision [10], natural language processing [11], image processing [12], speech recognition, signal classification, and battery estimation [13]. This study's key contribution can be summarized as follows:

1. The new dataset of the total of 1176 damages consists of 133 concrete deterioration cases, 483 roadways potholes, 360 roadway cracks, 100 roadway rutting cases, and 100 roadway lines from a different source open-sourced in GitHub

2. This is the first time that a deep neural network model is developed to categorize both bridge deterioration and road damages to the best of our knowledge

3. To extract high-level features from the data and shape the feature map to identify the damages, the custom shallow CNN models are explicitly designed

4. The Xception and AlexNet model is used as a transfer learning model due to the less available data for training

5. The ensemble model is developed using the custom CNN, Xception, and AlexNet to improve the prediction rate and achieve better performance using the different sets of feature maps

6. To verify the algorithm's accuracy and validity, the proposed models are compared with various methods

The remaining part of the paper is structured as follows. Section 2 is a literature review in which we look at other current techniques that prompted us to pursue this path. Section 3 presents materials and methods which elaborate the dataset, data augmentation, and region-based segmentation. Section 4 offers the proposed work to discuss custom CNN, transfer learning, and an ensemble model. Section 5 illustrates the result and discussion of the different state-of-the-art models with the proposed model followed by the conclusion in Section 6, which summarizes this paper.
2. Related Works

Maintenance of the infrastructure should be carried out regularly and extensively. Moreover, it is expensive in labor and material requirements. Therefore, infrastructure monitoring systems allow people to monitor and exchange information on problems with local infrastructures, such as graffiti, broken pavement slabs, and potholes and focus on nonworking street lights by using a similar set of images. Local municipal governments presently have the accountability of monitoring and maintaining all of their facilities. Many local governments in countries cannot carry out adequate examinations due to a lack of economic and human resources. To address the issues concerning infrastructure maintenance, these challenges must be solved as the local government controls most infrastructure. In a real-world situation, when road surface supervisors from a government play a major role to fix the harm of roads, they need to understand, with clarity, what kind of harm is involved and they need to take appropriate action. This section provides a detailed review of the existing techniques for road damage detection. Civil infrastructure and its damage detection are as follows. This experiment focused on the histogram and extracted the image region function and then added a nonlinear SVM kernel to detect the target. The results revealed that the pothole could be easily seen in this analysis.

In [14], the author proposed a neural network-based method for sensing harm using modal properties is introduced, which can take into account the pretending faults in the limited component-based model from which training designs are to be produced. The feasibility of the proposed approach is given two numerical comparisons on a simple beam and a multigirder bridge. Using a backpropagation-based neural network, the researcher demonstrated a method for determining the damage intensities in parts in truss bridge systems [15]. The technique used to solve problems related to several unidentified limitations in a substantial structural design is identifying the substructures. The natural dynamic characteristics and vibration frequency were provided to the neural network as input constraints for classifying the damage, primarily in irregular modal analysis measurements. The machine learning approach’s recent growth has given researchers more input to project different algorithms to classify and categorize the road harms using images of the road surface. In [16], the author introduced a method for restructuring the road summary using vehicle responses. An artificial neural network-based method was developed to rebuild the road’s surface area from the speed of vehicles. In this method, numerical procedures were created using different rates based on the irregularity grades, increasing defects for varying noise levels, and loads of cars. But this approach is particular for specific applications. The author proposed laser scanning and imaging of the pavement [17]. Automatic detection of cracks was implemented using a backpropagation-based neural network (BPNN) [18]. An image processing framework was developed to preprocess the images and mine the information about cracks. This framework was used to eliminate redundant information during the initial stage of image processing and applied feature parameters to categorize the gaps in the road images and differentiate linear and alligator or crocodile cracks. Japan road association-maintained road surface safety monitoring was primarily founded on graphical evaluation by professional road surface supervisors and objective determination by broad-scale inspection. This framework can address different large-scale images.

In [19], the author made a study analysis, rather than using a smartphone accelerometer. Researchers aim to achieve automated assessment of road surface conditions by taking images of the road surface using a mobile phone camera. To resolve the identification of the injury, several methods for measuring road surface damage from road surface images have been suggested. The author suggested using a commercial black box camera to locate potholes [20]. The pothole detection structure collects the data, such as location, appearance, and height using the camera. Damage occurs on the road surface, classified into nine crack forms. Cracks in the lane joint, hairline cracks, cracks in the edge, reflective cracks, widening cracks, shrinkage concrete cracks, joint cracks in the borders, and crocodile cracks are also called alligator cracks, crescent, or slippage cracks. These cracks may occur due to unstable soil roads. Their sewage system is not in good condition; there are poor execution of the job and lousy paving materials, which cannot tolerate the road’s capacity and traffic [21]. However, labor-intensive approaches, including thorough inspection, require a substantial amount of time and effort. Additionally, the labor-intensive method appears to be confused and unmanageable; hence, it implies a more significant risk. Though detailed inspection, such as MMS and scanning via laser, is highly efficient, thorough inspection requires too much expense. A detailed survey is done, and an application is built using a lightweight road manager smartphone [22].

An Android-based approach finally incorporates the model parameter at every investigation and classifies the road infrastructure images. Cracks and their different types need different kinds of maintenance and repair mechanisms images were gathered, and numerous procedures were applied to extract the significant features to highlight the cracks. The logarithm-based transformation was used to make the darker cells expand and brighter cells compress. Initially, preprocessing was done on images. Later, the decision tree-based heuristic algorithm was executed on the preprocessed images to classify and detect the crack on the photos. We compared the accuracy and runtime speed of state-of-the-art object detection methods using convolutional neural networks to train the harm detection model with our dataset using a GPU server and a smartphone. Finally, we show that the type of damage can be accurately classified into eight categories using the proposed object detection method (33A vibration-based system using the mobile accelerometer) and gyroscope is developed for automatic pavement distress detection, as opposed to a vision-based approach using video processing, which is proposed in this work. The vibration-based device has an accuracy of 80% in detecting potholes, patches, and bumps. For detecting gaps, potholes, and patches, the vision-based approach has
3. Materials and Methods

3.1. Dataset Collection. To build and validate the proposed method, the dataset was created from scratch. To highlight the generality of the proposed solution, photographs from various sources relevant to civil infrastructure were helpful. The damage databases currently available do not include Indian roads and bridge structures. The authors photographed most of the damaged buildings, and photographs of the damages in designs available on the Internet in the public domain were also used. Photos obtained from Google image searches are among the other sources used. The images collected from diverse sources were hand-labeled by the authors. The total number of images is 1176, containing 133 concrete deterioration, 483 potholes images, 360 crack images, 100 rutting images, and 100-line images. The dataset’s information is described in Table 2. Figure 1 shows some of the dataset’s sample photos.

3.2. Data Augmentation. Deep learning neural network provides better accuracy when trained with a vast dataset. To improve the network’s performance, the training data are augmented using the different image augmentation techniques from the existing data using the Keras deep learning. The newly created images belong to the same class as that of the original image. Image augmentation using transforms such as horizontal flipping, vertical flipping, rotations, and clipping, and shifts was performed to enhance and expand the dataset with new images. Although deep learning algorithms can learn features invariant to their location in the photo, the data augmentation can aid the model in learning components that are also invariant to transforms, such as light levels in photographs, ordering, and more. Some of the image augmentation results are shown in Figure 2, where the horizontal flipping, vertical flipping, clipping, and 90° rotation are performed.

3.3. Region-Based Image Segmentation. Segmentation of the additional damages was done based on the pixel values. The cracks were segmented based on multiple threshold values. The pixel-based segmentation is less complex as the computations are more straightforward and produce faster results. Pixel-based image segmentation is shown in Figure 3 which shows the image after pixel-based segmentation.

4. Proposed Deep Learning Framework

The proposed deep learning framework is shown in Figure 4. The data obtained are preprocessed. In the preprocessing stage, the image segmentation technique is used to extract useful features from the input image. The preprocessed images are fed into the three models where the first model is developed from scratch. The second model employed the pretrained (AlexNet and Xception model). The third model is the ensemble model of all three models to improve the proposed work’s performance. The ensemble model uses the majority voting scheme to predict the output.

4.1. Convolutional Neural Network. Convolutional neural networks (CNNs) are a form of feed-forward neural network used primarily for image classification. A CNN is made up of 3 layers: a convolutional layer, a pooling layer, and a fully connected layer. In general, images are fed into convolutional layers in a CNN. After the operations in the “convolutional kernel,” the output is fed into the pooling layers for downsampling, where the convolutional production is a feature chart. The primary part of CNN is a layer used to extract the features from the given input images. The process of forwarding propagation in each kernel is represented in

\[ a_k^l = \sigma(z_k^l) = \sigma(a_k^{l-1} * W_k^l + b^l), \]

where \( \sigma(z_k^l) \) is the activation function, \( W_k^l \) represents the convolutional weight kernel, \( b^l \) represents the bias in layer \( l \), and \( a_k^l \) represents the output of kernel \( k \) from layer \( l \). The output convolutional layer could be computed as follows:

\[ a^l = \sigma(z^l) = \sigma \left( \sum_{k=1}^{M} z_k^l \right) = \sigma \left( \sum_{k=1}^{M} (a_k^l * W_k^l) + b^l \right). \]

Followed by the convolutional layer, the pooling layer is used to reduce the feature dimensionality. The pooling function may be max, min, or average. However, max-pooling is widely used as it reports maximum output in the output field. The activation function is the most important
part of CNN because it is responsible for deciding the network’s output and computational performance. It also has a considerable effect on convergence speed. There are different activation functions such as sigmoid, tanh, ReLU, LReLU, PReLU, Swish, and softmax. Rectified Linear Unit is the most widely used activation function in deep learning applications. It provides the advantages of training an algorithm considerably fast by converging the weight updates quickly. Generally, in the output layer, the sigmoid function is used for binary classification, and softmax is used in

<table>
<thead>
<tr>
<th>S. No</th>
<th>Ref</th>
<th>Model used</th>
<th>Merits</th>
<th>Demerits</th>
</tr>
</thead>
</table>
| 1     | [1]  | CNN Model                                      | This model detects the damage location and damage severity with a validation accuracy of 89.06% | (i) But the model is implemented with the static condition  
(ii) The bridge is temporarily closed and determined using static loading conditions  
(iii) This can be expanded for the dynamic loading condition |
| 2     | [2]  | Fast R-CNN                                     | Data augmentation gives a better mean F1-Score of 6.255 when compared with R-CNN 6.174 | Much weightage is given for the preprocessing techniques model evaluation training is not discussed |
| 3     | [14] | Neural network-based damage detection method   | Efficient method for pattern detection                                | (i) A considerable amount of false alarms  
(ii) Structural damages of the bridges are not identified properly |
| 4     | [19] | FCN-based road surface anomaly detection model | The road anomalies and the location detection can be given approximately | But the depth of the anomalies cannot be determined by the proposed model |
| 5     | [27] | A black box camera is used to detect a pothole | (i) Potholes detection  
(ii) Suitable for pavement management system | (i) Black box camera uses a limited computing environment. The intensity of the light affects the false detection |
| 6     | [28] | Decision Tree heuristic algorithm              | Pavement crack detection                                             | (i) More processing time due to preprocessing of images  
(ii) Horizontal and vertical classification of pictures needed for further crack detection |
| 7     | [29] | SSD inception V2 and SSD MobileNet             | Developed for classifying eight types of road damages                | (i) Could achieve a precision of 77% and recall of 71% only  
(ii) Dataset consists of comparatively fewer pothole images |
| 8     | [30] | Vibration sensor-based method                  | It can be implemented using smartphones with sensors                | (i) The results are with low accuracy  
(ii) The vehicle’s suspension and speed affect the amplitude vibration and the accuracy |
| 9     | [24] | Machine learning (ML)-based approach           | Less computational and time complexity compared to deep learning models | (i) Hand-picked feature extraction using traditional image processing methods  
(ii) Machine learning models produce less accurate results than deep learning models |
| 10    | [20] | Image processing-based crack detection         | Cost-efficient and fast                                              | (i) There is only one form of damage found  
(ii) This leads to a high error rate in the presence of poor illumination and distortion |
| 11    | [25] | Machine learning (ML)-based approach           | Less computational and time complexity compared to deep learning models | (i) Only for pothole detection  
(ii) The results of machine learning models are comparatively lower than the deep learning models |
| 12    | [26] | Encoder decoder architecture of SegNet DeepCrack| This can be used for edge detection and images and vessel detection in retina images | The accuracy can be improved; it produces a 0.87 F-measure |

<table>
<thead>
<tr>
<th>Damage type</th>
<th>Number of images</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concrete deterioration in bridges</td>
<td>133</td>
</tr>
<tr>
<td>Roadways potholes</td>
<td>483</td>
</tr>
<tr>
<td>Roadways cracks</td>
<td>360</td>
</tr>
<tr>
<td>Roadways rutting</td>
<td>100</td>
</tr>
<tr>
<td>Roadways lines</td>
<td>100</td>
</tr>
<tr>
<td>Total</td>
<td>1176</td>
</tr>
</tbody>
</table>

Table 1: Overview of the literature survey.

Table 2: Dataset distribution.
multiple types. The softmax function is used in the output layer of the proposed CNN model, which is defined by the following equation for $n$ numbers $x_1, \ldots, x_n$ is given in

$$s(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}}.$$ (3)

The output ranges from 0 to 1 and adds up to 1 at the prediction stage.

4.2. Custom CNN Model. To have robustness in the model, the convolutional neural network model was developed from scratch by considering that the intense network may lead to longer training time, and a minimal network may result in poor learning. By considering these issues, the custom CNN model is proposed, and the structure is mentioned in Table 2. The input image size is resized to $64 \times 64$ width and height, respectively. The convolutional layer has a fixed kernel size of $3 \times 3$, but with a different number of filters with 16, 32, and 64 as the depth of the architecture progresses. The number of filters increased to extract the different sets of features. The flattening layer is used on the fully connected layer to convert a 2-dimensional image to a single-column vector. The softmax layer is used as the classification layer to classify the five different sets of classes. The optimization function used in the model is Adaptive Momentum Estimation (ADAM) to avoid local minima [31]. ADAM optimization function also supports adaptive learning using the network parameters. The categorical cross-entropy loss function used in the model as the problem is a multiclass classification problem. Table 3 summarizes the structure of the proposed network. The overall architecture is shown in Figure 5 to classify the damages in the civil infrastructure.

4.3. Transfer Learning Model. Transfer learning is a technique where the pretrained models are used instead of developing a scratch model. Transfer learning is where the pretrained models are trained on the ImageNet dataset consisting of millions of images. It can be used in feature extraction from the dataset followed by the flattened layer of CNN, and also, the pretrained models can be used as the classification network. In this proposed work, the Xception model is used for feature extraction. The Google inception architecture inspires the Xception model. The inception paradigm is interpreted in an “extreme” way in Xception. The Xception architecture is a depth-wise separable convolution layer stack with residual connections that are linearly stacked. Xception architecture uses depth-wise convolution instead of regular convolutional. The depth-wise convolutional reduced the training time by significantly reducing the parameter count. The Xception model is used as the feature extraction and used as the transfer learning model and given as input to the fully connected layers. It is shown in Figure 6. The output layer uses the softmax activation function to classify the given five classes.

The transfer learning model is also used in the AlexNet model, where it is used as the function extractor unit. Alex Krizhevsky had suggested it. It is a basic CNN structure made up of convolutional and ultimately linked layers. The input dimensions are $227 \times 227$ pixels. The first convolution layer receives the data. There are four more convolution layers after that. In the convolution layers, the activation feature used is ReLU. The softmax activation feature is used in the output layer. The AlexNet architecture for image classification is shown in Figure 7.
5. Results and Discussion

The experiment was performed in the Google Colab GPU runtime environment platform using Keras and Tensorflow. The three convolutional network architectures’ performance is compared with the ensemble CNN architectures and other state-of-the-art architectures for classifying the civil infrastructure. The entire dataset is split into the training and testing ratios of 90% and 10%. The training data contains 1027 images, and the validation data includes 153 images. Later, the training data is processed for data augmentation to enhance the training dataset. The accuracy of the model with feature extraction using pretrained models like Xception and AlexNet is analyzed. The four models are trained and tested with the obtained dataset for multiclass classification. The hyperparameter fixed for the proposed models is a learning rate of 0.001, an epoch of 100, and batch size of 8, and an ADAM optimizer is used. The training data is used to train the custom CNN model, which is then tested with validation data. The data augmentation and pixel-based segmentation features are used to avoid overfitting in the model. Despite efforts taken to avoid overfitting by the regularization techniques, it was observed that the proposed custom CNN reached a convergence state between the scale of 80% and 86% of classification accuracy and began to memorize training data. The highest classification accuracy was observed at the 36th epoch as 86% for the validation dataset and it is shown in Figure 8. The model weight and bias from the 36th epoch are taken for model testing. Xception model is trained on the obtained dataset to classify bridge damages and road damage classification and obtained the training accuracy 96% and validation accuracy of 82% shown in Figure 9. The gap between the training and validation accuracy is quite high due to the dataset class imbalance problem. Similarly, for the AlexNet model, the training accuracy ranges between 92% and 96%, and validation accuracy is 84% due to the same class imbalance problem and interclass similarity in the dataset shown in Figure 10. In order to solve this problem, the ensemble model is developed from the three models by combining the architecture of custom CNN, AlexNet, and Xception models. The preprocessed dataset is fed into all three architectures at the same time in order to extract discriminative features from the feature map, and then, the majority voting scheme is used to distinguish the various types of damages. For the obtained dataset shown in Figure 11, the ensemble approach

![Figure 3: Pixel-based image segmentation of infrastructure images: (a) damaged roads and (b) cracked roads.](image)

![Figure 4: Overall framework of the proposed work.](image)
provides a training accuracy of 94% and a validation accuracy of 87%.

To assess the model’s robustness, all of the proposed models are compared to various state-of-the-art architecture. The proposed method is the only method trained and tested for various classes such as roadways cracks, lines, potholes, and rutting and bridge deterioration detection. But the model proposed in the literature is trained and tested with specific damages, either road damages for crack or pothole and bridge damage detection; they were not specific to Indian roads. The performance analysis of the different models with the proposed method is shown in Table 4.

Table 4: Structure of custom CNN model.

<table>
<thead>
<tr>
<th>Layer</th>
<th>Layer type</th>
<th>No. of nodes</th>
<th>Kernel size</th>
<th>Activation</th>
<th>Dropout rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Input shape</td>
<td>64 × 64</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>1</td>
<td>Conv1</td>
<td>16</td>
<td>3 × 3</td>
<td>ReLU</td>
<td>—</td>
</tr>
<tr>
<td>2</td>
<td>Conv2</td>
<td>16</td>
<td>3 × 3</td>
<td>ReLU</td>
<td>—</td>
</tr>
<tr>
<td>3</td>
<td>Max-pool</td>
<td>—</td>
<td>2 × 2</td>
<td>—</td>
<td>0.2</td>
</tr>
<tr>
<td>4</td>
<td>Conv3</td>
<td>32</td>
<td>3 × 3</td>
<td>ReLU</td>
<td>—</td>
</tr>
<tr>
<td>5</td>
<td>Conv4</td>
<td>32</td>
<td>3 × 3</td>
<td>ReLU</td>
<td>—</td>
</tr>
<tr>
<td>6</td>
<td>Max-pool</td>
<td>—</td>
<td>2 × 2</td>
<td>—</td>
<td>0.2</td>
</tr>
<tr>
<td>7</td>
<td>Conv5</td>
<td>64</td>
<td>3 × 3</td>
<td>ReLU</td>
<td>—</td>
</tr>
<tr>
<td>8</td>
<td>Conv6</td>
<td>64</td>
<td>3 × 3</td>
<td>ReLU</td>
<td>—</td>
</tr>
<tr>
<td>9</td>
<td>Max-pool</td>
<td>—</td>
<td>2 × 2</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>10</td>
<td>FC</td>
<td>512</td>
<td>—</td>
<td>—</td>
<td>Softmax</td>
</tr>
<tr>
<td>11</td>
<td>Output</td>
<td>5</td>
<td>—</td>
<td>Softmax</td>
<td>—</td>
</tr>
</tbody>
</table>

Table 4 in the Resnet model is presented to classify the pothole in the road and achieves an accuracy of 90.5% of classifying pothole and nonpothole using thermal photos [32]. From the confusion matrix discussed in the literature, the precision and recall are calculated as 87.2% and 80.2%. The traditional image processing techniques have been used in classifying the pothole in the road, as proposed in [33]. The overall accuracy of the model is achieved as 73.5%. The precision and recall of the method are 80.0% and 73.3%, respectively. The proposed ensemble model provides an accuracy of 87% for the obtained dataset. It also achieves better precision and recall of 84.92% and 83.53% compared to other proposed models in this work. The Resnet [32] model and ANN [34] in the table provide better accuracy when compared to all other models because the models were trained on the dataset to classify potholes or nonpotholes in
the road. Road damage is detected using CNN-based methods and achieves an accuracy of 81.4% [23]. But the proposed method is trained on the multiclass dataset with different inter- and intraclass similarities. The graphical representation of the above-discussed process is shown in Figure 12.

The overall runtime of the other pretrained models is provided in Table 5. The training time is calculated in seconds for each epoch of the model trained on the obtained dataset. By considering the best three models, the AlexNet, Custom CNN, and Xception net are considered for the proposed problem.
Figure 9: Accuracy and loss with Xception model.

Figure 10: Accuracy and loss with AlexNet-based CNN model.
Table 4: Performance analysis proposed method with the different models.

<table>
<thead>
<tr>
<th>Ref</th>
<th>Classification types</th>
<th>Methods</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>[32]</td>
<td>Pothole classification</td>
<td>ResNet18</td>
<td>90.5</td>
<td>87.2</td>
<td>80.2</td>
</tr>
<tr>
<td>[33]</td>
<td>Pothole classification</td>
<td>Image processing</td>
<td>73.5</td>
<td>80.0</td>
<td>73.3</td>
</tr>
<tr>
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<td>72.7</td>
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<td>[34]</td>
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<td>85.7</td>
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<td>[23]</td>
<td>Road damage detection</td>
<td>CNN</td>
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<td>82.9</td>
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<td>Ensemble model</td>
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Figure 11: Accuracy and loss with ensemble transfer learning model.
6. Conclusion and Future Scope

Maintaining the civil infrastructure in a country like India is a challenging task. It is time-consuming and requires a lot of skilled workforces to identify the damages. In this regard, it is very significant to introduce a system to analyze the damages and detect them automatically based on vision-based techniques. Although successful strategies are available for road damage detection, they were not specific to Indian roads. In this proposed work, other civil infrastructure damages like bridge damages were also considered. The pretrained CNN architectures like Xception and AlexNet were used in the proposed work for transfer learning. To obtain more knowledge from each sample, the training data was expanded by the data augmentation method. At the end of this study, the ensemble transfer learning model’s accuracy value was measured as 87.1% on the test data not seen before by the model. It is predicted that higher accuracy can be achieved by adding more and more unique samples to the train data.

In the future, the dataset will be augmented using advanced techniques like undersampling and oversampling to reduce the dataset imbalance problem. Further, the proposed model will be deployed in the unmanned aerial vehicle to monitor the road damage condition and bridge condition during the natural disaster without risking human life.

Data Availability

The data used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References


