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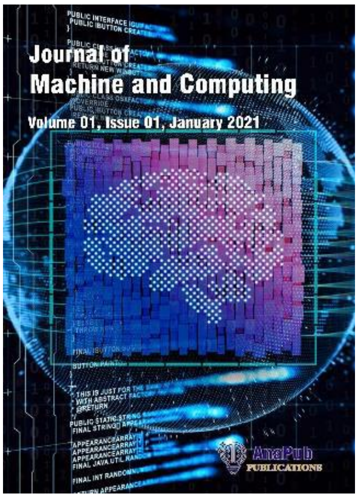

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A Road Damage Detection based on Contrast Limited Deep Convolution Neural Networks for Urban Roadways

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Abstract

Road crack detection is a crucial safety measure for any country, especially in regions with complex road networks. In India, most roads are well-connected to cities and urban areas. However, urban roads often suffer frequent damage due to various factors. This study focuses on detecting road damage in Indian urban areas using a Deep Convolutional Neural Network (DCNN). We have developed a model specifically designed for identifying cracks in Indian urban roads. To evaluate the proposed model, we collected over 700 images of damaged roads from different urban locations across Tamil Nadu. In this work, we employed the DCNN algorithm for road crack detection, which has proven to be an efficient approach. The proposed method incorporates Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance the contrast of road images. This is the first initiative aimed at developing a road damage detection system tailored to urban roadways in India. A comparative analysis was conducted during the preprocessing stage by applying both HE and CLAHE techniques. The model was trained using 5,000 roadside images, including both cracked and non-cracked surfaces. During training, image enhancement was performed using HE and CLAHE, and the processed images were then used to train the DCNN. For testing, 700 roadside images (with and without cracks) were utilized, following the same preprocessing steps. The model's accuracy was determined based on its ability to correctly identify road cracks. Results indicate that the proposed model performs effectively for crack detection on CLAHE-enhanced images of Indian urban roads. Additionally, the proposed model's performance was compared with existing models such as ResNet, VGG16, and VGG19 using the same dataset. Evaluation metrics including accuracy, precision, recall, and F1-score were used. The proposed model achieved 98.6% accuracy, 98.5% precision, 99.6% recall, and a 99% F1-score

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Keyword: road damage detection, urban roads, Convolutional Neural Network, Deep Learning

1. INTRODUCTION

Indian states are focussed on their road networks for improving road connections establishment, rework, and major repairs. Due to the growth of larger transportation between states in India, government has invested high cost for road establishment and maintenance. Recent years, many researchers have been published many research article for automation in road damage detection using machine learning and deep learning with large size of data samples. In case, we have only minimum training samples for training the system would be a complex and timing consuming process.

Regular road inspection through physical monitoring is time consuming process and costly one. Now a days, semi-automated inspection mechanism used to get the accurate and current information about the road surface condition to maintain high quality standards in a efficient way with minimum cost involvement. When evaluating the road quality, surface measurement is a crucial and important factor for crack identification. The following factors are commonly used to quantify the road cracks, crack type, length of crack, and severity level of crack and identify the source of cracks. Initial stage of inspection, identifies the cracks well in advance and this allow one to perform a proper maintenance. Initially and allow. Road damage is happened quite gradually on the road surfaces

During the initial 75 percent of their lifespan, road surfaces experience a 40 percent decline in quality. However, if left untreated, the decline in quality becomes more pronounced due to water infiltration and ongoing usage, resulting in another 40 percent reduction during the subsequent 12 percent of their life. Road management programs can identify roads with early signs of deterioration, allowing for cost-effective preventive maintenance measures to be implemented, which can reduce expenses by a factor of 5.

Cracks are the most commonly known dangerous defects in any regular structures, such as bridges, pressure vessels, mining equipment, aero-engines, etc. Any unnoticed cracks of key components will lead to accidents. Due to this reason, it is mandatory to monitor the integrity of structures and evaluate the crack for safety.

The categories are classified based on the human involvement for crack detection into three types, fully automatic, semi-automatic and manual. In a real world scenario, manual visual inspection is the primary source of inspection and most widely used technique in structure integrity monitoring. This process will be a very expensive and time-consuming process. However, the accuracy of detection highly depends on the experience and attention of technicians involved in the detection process, and the cracks are easy to be missed. Since, to improve the efficient and reliability in the inspection process, we have to developed an automatic technique to detect cracks.

In a fully-automated technique, we need high-quality images for training and testing the crack identification. We need a high resolution camera for obtaining the highest quality road images and the output of a crack detection system mostly depends on the quality of the image. The high quality image can give better accuracy as well as better visualization for crack detection. The most commonly identified types of cracks occurring on roads which are longitudinal crack, alligator cracks, transverse crack, diagonal crack and edge crack.

The presence of cracks in road surfaces indicates the initial stages of degradation. By detecting these cracks early on, proper maintenance can be initiated through timely repairs, resulting in cost savings. This proactive approach prevents the need for more extensive and costly repairs that would be required if the road condition worsened or suffered further damage.

2. RELATED WORK

In the article [1], it is stated that the learning stage for crack recognition, specifically for default identification, is not necessary. Instead, a substitution approach utilizing Free-Form Anisotropy (FFA) is proposed for crack identification. The process involves four phases: pre-processing, segmentation, post-processing, and classification, which are commonly employed in crack recognition. Conditional Texture Anisotropy (CTA) is utilized, where cracked pixels exhibit high CTA values while defect-free pixels show low values. A dual-level thresholding technique is applied, and the results of both CTA and FFA are compared. The proposed approach demonstrates better outcomes in crack identification, capable of detecting cracks as small as one millimeter in any orientation. In the article [2], an automated system for crack detection and classification is proposed. The system focuses on determining road properties based on the presence of cracks, which is used to estimate the formation of cracks on the road surface. The cracks identified using these techniques are characterized as miniature cracks. Algorithms such as Djikstra's shortest path algorithm are employed in the process.

The Crack Tree approach [3] is an automated method for crack recognition in road surface images. The process involves several steps. Firstly, shadows within the image are identified, which helps enhance the discrimination of cracks. Then, a tensor-based strategy is employed, which creates a map consisting of crack openness and coherence. Subsequently, Minimum Spanning Trees (MSTs) are constructed to represent theanalyzed cracks. Undesired edges are pruned, resulting in the formation of crack contours. The developed strategy is evaluated using a dataset comprising a mixture of images containing both cracks and non-cracks. Through quantitative and qualitative analysis, it is shown that the proposed Crack Tree approach achieves higher accuracy compared to existing edge and crack detection methods.

In the proposed strategy discussed in another article [4], a dataset is employed that undergoes various image processing techniques such as image smoothing, path detection, power normalization, enhancement, and crack detection. Image blocks of pixels are utilized to determine the type of cracks present. Additionally, image smoothing techniques are applied alongside the aforementioned methods. Preprocessed images are then partitioned using a dual threshold, which is calculated specifically for each image, in order to separate cracks from the background.

The paper [5] introduces a methodology for crack detection by analysing the subtle differences between each pixel in an image with a length of d [5]. This approach relies on 2D Continuous Wavelet Transform (CWT) followed by Markov random field segmentation. The method has been tested on a high-resolution database of real images. The algorithm [6,7] consists of several steps, including endpoint selection, minimal path estimation, and path selection. It was assumed that only five methods yield the best results. The proposed technique combines particle filters and machine vision, where the particle filter is used for crack detection using the RGB and HSV color models, while machine vision techniques are employed for crack measurement algorithms. Experimental results showed that the proposed method achieved an image processing time of 2 seconds and an estimation time of 6 seconds.

Cracks and obstacles are detected by equipping a vehicle with cameras and sensors, and its movement is controlled [8]. Another dynamic method for road crack identification is presented, utilizing image scanning transformation inspection and simultaneous discriminant analysis. In the initial stage, the road image is filtered using bilateral and median filters. After obtaining a grey scale image, crack regions are removed by calculating the test transformation of the image. The cracks are then eliminated using differential analysis, such as Otsu's binarization technique. 200 road surface images containing cracks, as well as some images without cracks, were utilized for testing.

The minimal path calculation technique considers two factors: the cost function and optimization [9]. The methods used involve defining constraints and selecting a subset of sources and destinations. A Decision Tree is a model that establishes a relationship between certain data features and their corresponding outcomes [10]. Utilizing a decision tree for the classification process is feasible by obtaining various feature data. The acquisition of images plays a crucial role in determining the color of a road surface. The presence of cracks on the surface is detected using image enhancement techniques, such as median filtering. After performing morphological operations, cracks are classified using a decision tree. Experiments conducted using this process demonstrated its real-time applicability.

Deep Neural Networks (DNN), also known as Deep Learning, do not require feature extraction as they learn directly from raw image data [11]. Visual information, such as images and videos, in Deep Convolutional Neural Networks (DCNNs) is highly dynamic. The three layers in deep CNNs are convolution layers, sub-sampling layers, and pooling layers. High predictive accuracy is achievable only when large image datasets are available. An algorithmic program was used to determine whether to include sets of crack candidates for merging. Cracks with a width of less than two metric units are assigned severity level one, while cracks wider than two metric units are assigned severity levels two or three. The Matlab algorithm implementation was supported by the tools.

The Minimal Path Selection (MPS) technique suffers from high computing time. However, this technique has been improved to provide robust and precise segmentation of cracks in pavement images [12]. It not only reduces computing time but also enhances overall performance. A Bayesian methodology for asphalt crack identification has shown promising results, particularly in non-linear cracks [13]. The process begins by obtaining image data from a road imaging system, followed by preprocessing the image using an erosion technique. Finally, a particle filter based on a geometric model, specifically the Sequential Monte Carlo particle filter, is utilized. Road crack detection can be viewed as both non-probabilistic and probabilistic. The accuracy of the method is determined based on the proximity of the estimated condition of the crack pixels. On average, the entire crack can be traced in less than 5 seconds.

A Convolutional Neural Network (CNN) is a deep learning algorithm that takes an image as input, identifies important features, and applies filters to distinguish them from each other [14]. The preprocessing required in a CNN is relatively lower compared to other classification algorithms. Traditional methods are typically hand-designed, requiring extensive training. However, CNNs have the ability to learn these features. By utilizing relevant filters, CNNs can effectively capture spatial and temporal conditions within an image [15]. The performance of a CNN can be improved by utilizing reusable weights and reducing the number of parameters in the image dataset. Using CNN, the system can be trained to understand the intricacies of the image.

Image binarization converts pixels in a grey scale image into black or white [16]. The input image is divided into sub-images, and image binarization assigns black colour to cracks and white colour to non-crack objects within the image. The CNN-based procedure proved to be more accurate and cost-effective compared to the Speeded Up Robust Feature (SURF) based procedure. The CNN-based procedure demonstrated better overall performance than SURF-based methods.

A U-Net deep learning network was used for pixel-wise road crack detection, and various network configurations were compared to determine the best configuration [17]. The number of layers in the network ranged from 2 to 4, kernel sizes of "3x3," "5x5," "7x7," and "9x9" were evaluated, and the number of features ranged from 33 to 64. The performance was evaluated on the CrackForest dataset. The experiments showed that the network with 64 kernels performed better compared to any architecture with 32 kernels. The neural network configuration L3 5x5 performed similarly to the best-performing network, L4 5x5. Evaluation of computational speed revealed that the network runtime increases significantly with larger kernel filter sizes.

The proposed algorithm in paper [18] introduces a sample and structure guided network for road crack detection. The task is considered as a pixel-wise classification problem, aiming to obtain a salient crack map directly from the raw road image. The algorithm utilizes Focal loss to guide the learning process and address the optimization problem caused by imbalanced data. Additionally, the paper proposes a series of image enhancement strategies to enhance the generalization capability of the method on other open datasets, increasing its practical value. Experimental results on three public datasets and a photographed dataset demonstrate the robustness, effectiveness, and superiority of the proposed algorithm.

A unique road crack detection algorithm [19] based on deep learning and adaptive image segmentation is presented. The approach involves training a deep convolutional neural network to classify input images into positive (crack present) or negative (crack absent) categories. The positive images are then processed using a bilateral filter to reduce noise while preserving the edges between cracks and the road surface. Finally, the filtered images are downsampled, and cracks are extracted using an adaptive thresholding method.

A teachable convolutional method [20] proposed a technique for crack detection in complex environments. The algorithm successfully identifies crack data in unpredictable situations and achieves state-of-the-art accuracy. The classification precision for transversal and longitudinal cracks exceeds 95%, and the accuracy for square and crocodile cracks is above 86%, compared to manual classification results.

In the context of road maintenance, the use of automatic techniques for crack detection is preferred due to their high efficiency and cost-effectiveness [21]. The focus of the research is to develop a suitable technique for crack detection using Convolutional Neural Networks (CNN) that offers better accuracy compared to existing technologies. The research also addresses the classification of cracks.

The remaining part of the paper includes detailed information about the CNN model architecture used for the research, dataset details, and the flow of processes in Section 2. Section 3 presents the results obtained during the experimentation phase, including a comparison with other existing models. Section 4 concludes the paper and discusses the future scope of the research. Section 5 provides a list of references that were helpful in conducting the research.

3. PROPOSED MODEL

We have developed a road crack detection system by using Deep Convolutional Neural Network (DCNN) model for Indian urban road crack detection for the road side photos taken by using simple smart phase cameras. The proposed model trained with existing road cracking images along with Tamil nadu urban road damage samples. We have used grey scale and contrast limited images for the training and testing phases. The proposed model has two phases, the first phase we have train the model with existing road cracking samples using data augmentation. We have train the sample model with our own data samples taken from smart phone cameras. The training samples are pre-processed with image enhancement by applying contrast limitation techniques. In the testing phase, we have pre-process the input images with grey scale conversion and contrast limitation. In the next step, we have applied the DCNN classifier for classification of cracking and non-cracking road images by validating the input image. The figure 1 shows the phases involved in the proposed road crack detection model. The proposed design is implemented with following four phases, 1) Pre-processing Phase, 2) Classifier Phase, 3) Training Phase, and 4) Testing Phase

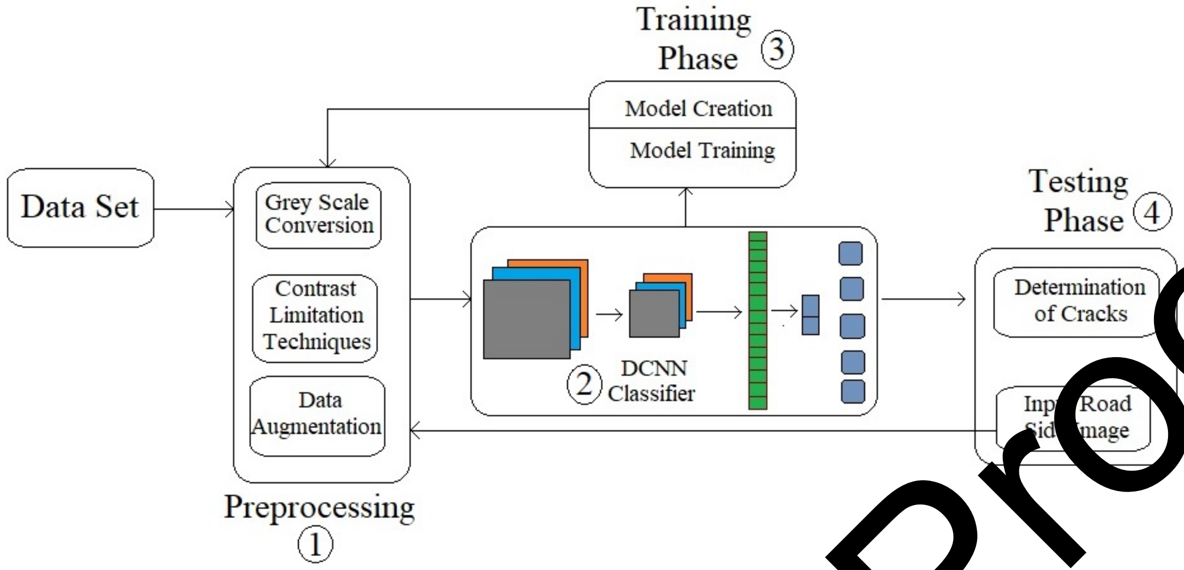


Figure 1: Proposed Road Crack Detection Model

a. Phase 1: Pre-processing

In the pre-processing phase, the training and testing samples are converted into grey scale images and improved or enhanced pixel quality. The pixel quality is improved by applying the contrast limitations techniques. The aim of pre-processing phase is to improve the road side image dataset that suppresses unwanted distortions or enhances some image features important for further processing. This phase includes with two steps, greyscale conversion and applies contrast limitations.

Greyscale Conversion

In the proposed scheme, we have used grey scale conversion for improving the contrast of image for easy tracking of cracks from RGB high quality images. In this process, the RGB images has been converted into grey scale image base on brightness value. The following equation consider the brightness value of RGB based on the high value from R, G, and B (equation 1).

$$V = MAX(R, G, B)$$

The grey scale values of images are concentrated in a narrow interval. The histogram equalization can be used to adjust the distribution of grey scale value to enhance the local contrast; the result of image will be more distinct in the crack and back ground areas

Contrast Limitation Techniques

Histogram Equalization

Histogram Equalization is an image processing method employed to enhance the contrast of images. Its objective is to evenly distribute the most common intensity values, effectively expanding the range of intensities in the image. By doing so, this technique typically enhances the overall contrast of images in cases where the usable data is represented by similar intensity values. Consequently, areas with initially lower local contrast can achieve a higher level of contrast.

Histogram equalization may lead to too brightness or too darkness in all the regions, because the contrast value is not limited. The contrast value of noise gets increased in the processed image. A Histogram of an image is represented as $h(i)$ in equation 1. Here n is the total number of pixels and L is the total number grey levels of image.

$$n = \sum_{i=0}^{L-1} h(i) \to (1)$$

$$\hat{h}(i) = pow(log\ log(h(i) + \alpha), \beta), 0 \leq i \leq L-1, \alpha > 1 \to (2)$$

To reduce the effect of large spikes in histogram, a simple equation is shown in equation (2) with the combination of logarithm and power. To avoid empty histogram bins, α is set larger than 1 and β is a parameter the of power function. In an experimental analysis α and β are empirically set to 2 for our proposed approach. Here, $h(i)$ and $\hat{h}(i)$ are original and modified histogram respectively.

Adaptive Histogram Equalization

Adaptive Histogram Equalization (AHE) is a technique used to enhance the contrast of image and this technique is differs from normal histogram equalization. In this method, the contrast value of pixels is enhanced locally. This method divides the image into distinct blocks and computes histogram equalization for each block. This method enhances the local contrast and definitions of edges in all distinct regions of the images.

Adaptive Histogram Equalization (AHE) is a pre-processing technique used in image process to improve the contrast rate of an image for clear view. In this technique, image has been divided into several sections and each section is computed with a corresponding histogram value. These values use to redistribute the luminance values of the image. This technique is more suitable for improving the local contrast and enhancing the definitions of edges in the each region of an image. AHE over amplifies the noise value of each region with respect to homogeneous regions of an image. We have use this technique to identify the cracking region of a road image by increasing the histogram values

Contrast Limited Adaptive Histogram Equalization (CLAHE)

We have used the Contrast-Limited Adaptive Histogram Equalization (CLAHE) to improve the image quality compare to AHE method. The AHE technique has some noise over amplifying problem, which may lead to over contrast in the input image

The unwanted noise problem associated with AHE can be reduced by limiting contrast level enhancement specifically in homogeneous areas. These areas can be characterized by a high peak in the histogram associated with the contextual regions since many pixels fall inside the same grey range. With CLAHE, the slope associated with the grey level assignment scheme is limited; this can be accomplished by allowing only a maximum number of pixels in each of the bins associated with local histograms. After clipping the histogram, the pixels that were clipped are equally redistributed over the whole histogram to keep the total histogram count identical.

The contrast factor is defined as a multiple of the average histogram contents. With a low factor, the maximum slope of local histograms will be low and therefore result in limited contrast enhancement. A factor of one prohibits contrast enhancement; redistribution of histogram bin values can be avoided by using a very high clip limit, which is equivalent to the AHE technique.

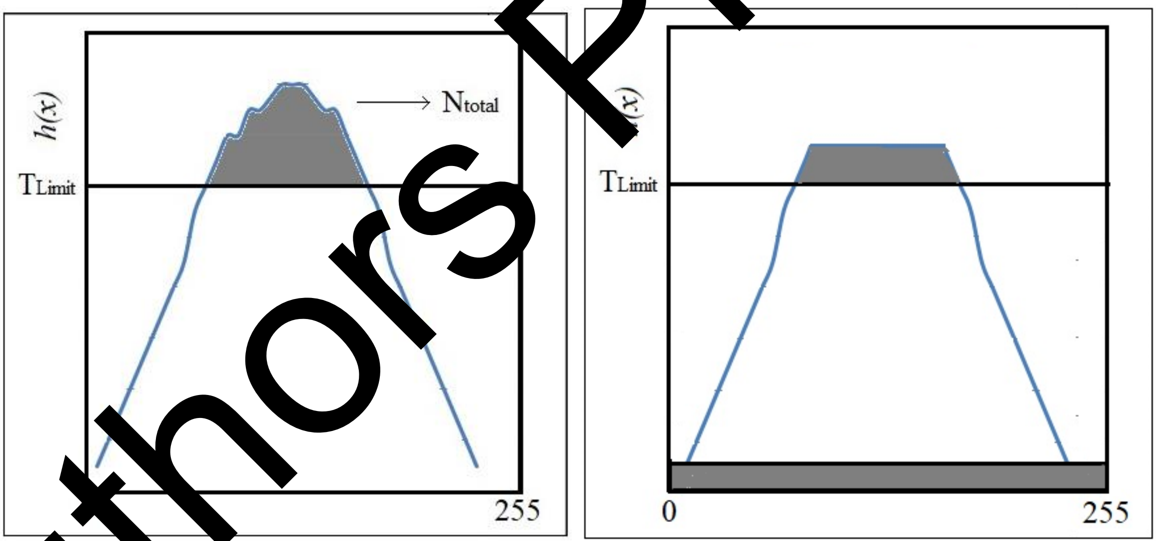


Figure 2: Contrast Enhancement in CLAHE

Figure 2 (a) and (b) shows two examples of contrast enhancement using CLAHE; although the image at the right was CLAHE processed using a high clip limit, image noise is still acceptable.

The main advantage of the CLAHE transform as presented in this Gem is the modest computational requirements, its ease of use and it produces excellent result for contrast limiting for most of the images

b. Phase 2: DCNN classifier

The basic DCNN image classification takes an input road side image, process it and classify the image under certain specified category (ex. Cracks and non-crack). The DCNN Model takes an image as an array of pixels. In DCNN model train and test phase, each input image will be passed through a series of convolutional layers with Filters (kernel), pooling, fully connected layers and apply Softmax function to classify an object with probabilistic values between 0 and 1. Following are the different layers used in the architecture to classify the image based on the values

In this work, DCNN classifierarchitecture has 3 convolutional layers with 3 max-pooling layers along with a flatten layer and two dense layers. For inputimage relu is the activation function used. Output is taken using sigmoid activation function.

The task at hand, although mimicking human behaviour, presents greater challenges for an automated system. One of the identified problems in the automated system is object detection and classification, particularly when it involves objects with varying perspectives [23]. Traditionally, a two-stage strategy has been employed to address this classification problem. Initially, feature descriptors and manually engineered characteristics were extracted from the images, which then served as input for a trainable classifier. For this study, we have used Deep Convolutional Neural Network (DCNN) models and this model given in the figure 3. We have used three other models for performance analysis and comparison ResNet, VGG16, and VGG19. The important step in the development process is to incorporate a database as input for training the DCNN models. This was facilitated by utilizing the Keras deep learning framework, which provides a convenient setup for the neural network. Keras, an Application Programming Interface (API), aids in the development and evaluation of deep learning models. The DCNN models were trained using the provided input samples and their performance was evaluated using the testing dataset (Table 1). The datasets of samples were fed into the DCNN models through the input layer and passed through convolutional layers, pooling layers, and fully connected (FC) layers. Subsequently, the input database was classified by the DCNN outputs using the Softmax activation function. The output analysis included precision, recall, F1 Score, and accuracy for crack detection. The VGG16 model, also known as the Visual Geometry Group 16 or Oxford Net, is a convolutional neural network architecture proposed by [24] from the University of Oxford. It consists of 16 layers, including 13 convolutional layers and three fully connected layers. The VGG16 model gained recognition after its participation in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2014, where it demonstrated remarkable performance in detection, classification, and segmentation tasks [24]

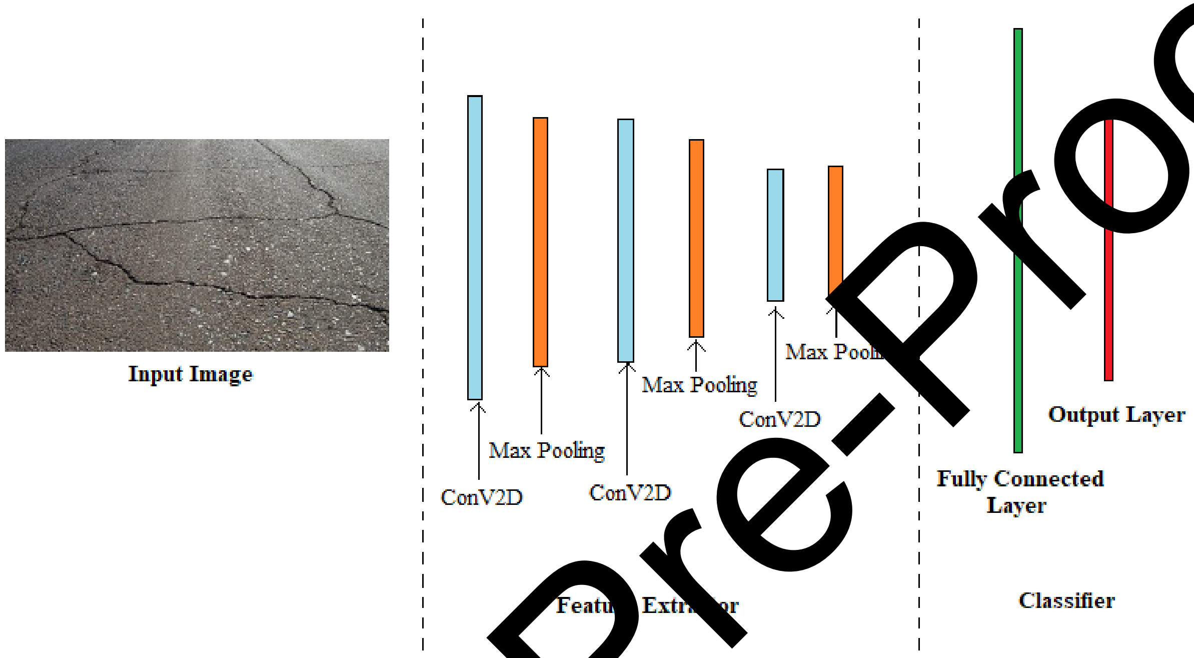


Figure 3: DCNN Classifier

c. Phase 3: Training Phase

In the training phase, we have used 5000 road side images of both cracking and non-cracking. The training samples are taken from the existing data set for road side images [25] and road damage images taken from the smart phone cameras. The training samples are labelled with cracking or non-cracking types. The image sizes are commonly fixed with 258X386. In this phase, we have used the following two processes continuously for training the DCNN classifier: pre-processing and Classification.

In this section, we have performed the pre-processing for all images that have been available and collected images from the smart phone cameras. In order to increase the dataset size and improve the performance of the Deep Convolutional Neural Network (DCNN), image augmentation techniques were applied. This involved rotating the images by 90° clockwise, 90° anti-clockwise, and performing perpendicular and vertical rotations. No image resizing was performed during the pre-processing phase. The images were labelled based on five types of pavement cracks: transverse crack, longitudinal crack, diagonal crack, edge crack and alligator crack. These labelled images were then saved in separate folders. Subsequently, the dataset [38] was created into two groups: training with available samples and collected samples. A detailed discussion about the proposed road crack detection model has been explained in the following algorithm as follows,

Algorithm: Road Damage Detection Based on CL based DCNN

Input: A set of road images $D_I = \{I_1, I_2, \dots, I_n\}$

Output: Detection and classification of road damages from each image.

Step 1: Data Acquisition

1. Collect road images from available datasets.
2. Annotate the images with bounding boxes for different damage types.

Step 2: Preprocessing using CLAHE

1. Convert each image $I_i \in D_I$ to grayscale.
2. Apply *Contrast Limited Adaptive Histogram Equalization (CLAHE)* to enhance local contrast as follows,
   a. Clip limit C set as 2 (based on the requirement).
   b. Apply *CLAHE* to each channel or block.

Step 3: Data Augmentation

1. Perform real-time augmentation to increase data variability as follows,
   a. Rotation, flipping, cropping, and scaling.
2. Ensure labels are transformed accordingly

Step 4: Deep Convolutional Neural Network (DCNN) Architecture Design

1. Choose a base CNN model for conducting classification (e.g., a custom CNN).
2. Modify the final layer to match the number of damage classes.
3. If detection is required, use models Faster R-CNN and YOLO with CLAHE-processed inputs.

Step 5: Model Training

1. Split the dataset D_I into T_I training, U_I validation, and TE_I testing data sets.
2. Compile the model with appropriate loss (cross-entropy) and optimizer (Adam).
3. Train the model on the augmented and CLAHE-enhanced dataset (Step 2 and 3).
4. Compute performance metrics like accuracy, Precision, Recall, and F1-Score.

5. Optimize the Training model with maximum number of iterations

Step 6: Evaluation and Testing

1. Evaluate the trained model by using U_I validation dataset.
2. Compute and analyze confusion matrix, precision, recall, and F1-score for damage identification.
3. Apply the trained model for road crack detection over a testing image fromTE_I.

Step 7: Output

1. Return predicted result of damage locations from testing dataset.

A detailed description of the dataset can be found in Table 1. For this study, 80% of the dataset was used for DCNN training, while the remaining dataset was used for testing. To ensure a balanced partitioning, an equal number of crack images were assigned to each type of crack category.

	Cracks	**Non-Cracks**	**Total**
Total number of Training Samples	3400	1600	5000
Total number of Available Training Samples	2100	900	3000
Total number of Collected Training Samples	1300	700	2000
Total Number of Testing Samples	550	150	700

Table 1: Details of Data set for Training and Testing

d. Phase 4: Testing

During the testing phase, we have used 700 collected image samples to identify whether an image contains a crack or not. The image first undergoes pre-processing, which involves converting it to grey scale and applying Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement. If the input Image is not compatible with the size of 256X386 then the image will be resized. The Deep Convolutional Neural Network (DCNN) model then takes the pre-processed image as input to determine whether it contains cracks. If cracks are detected, the image proceeds to the classification stage to determine the specific type of crack present

4. PERFORMANCE EVALUATION AND ANALYSIS

We have used the following system configuration for implement the proposed crack detection model Intel(R) Core(TM) i5-4590 CPU @ 3.30GHz 3.30 GHz and we have used a smart phone with high quality rear camera for road capturing side image. We have trained the images in the dataset were captured using a smart phone camera with the image quality of 108MP + 2MP + 2MP and manually labelled according to the type of crack. To enhance the contrast level of the collected images, we have used Histogram Equalization (HE) and Contrast-Limited Adaptive Histogram Equalization (CLAHE) techniques. Both the training and testing image datasets are pre-processed using the HE and CLAHE techniques. The performance of the proposed model evaluated by using these modified contrast images.

This research utilized a dataset comprising 5000 images for training phase alone. This dataset consisted of images containing both cracked and non-cracked surfaces. In the initial part of the research, a separate training dataset consisting of 5000 images was created. These images were sourced from various locations and included both cracked (3400) and non-cracked (1600) images. The training dataset was labelled with the corresponding crack types. The size of the training dataset amounted to approximately 59[illegible] MB. The training dataset focused on five common types of cracks: longitudinal, transverse, linear, crocodile, and diagonal. The primary objective of this research was to determine whether cracks were present or not, without specifically classifying the crack type. The testing dataset encompassed 700 images, comprising both cracking and non-cracking images. This dataset included images representing all types of cracks and was labelled accordingly. The test data set prepared with road damage images taken from urban road ways in Tamil Nadu. The performance analysis of the proposed method was evaluated based on the accurate classification of the cracking images within the testing dataset

a. Image Enhancement using Contrast Limitation Techniques

During the pre-processing phase, all crack and non-crack images are converted into grey scaled images and enhanced using Contrast Limitation techniques. The contrast limitation process carried out by using Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE).

The CLAHE method builds upon adaptive histogram equalization by dividing the images into small blocks or tiles and appropriately amplifying the intensity of black and white colors within each tile. By employing this approach, the enhanced images exhibit improved quality for crack detection. Consequently, the use of enhanced images results in a higher classification rate for the Deep Convolutional Neural Network (DCNN) compared to using the DCNN without any enhancement method. The following figure 4 shows the result of original grey scaled road cracking image, Histogram Equalized image and CLAHE image. The following image table shows the different types of road damage images taken from Indian urban road images,

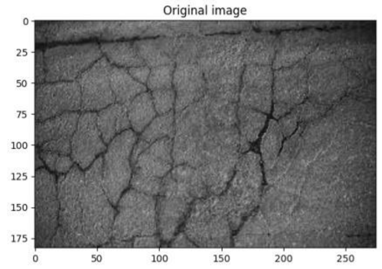
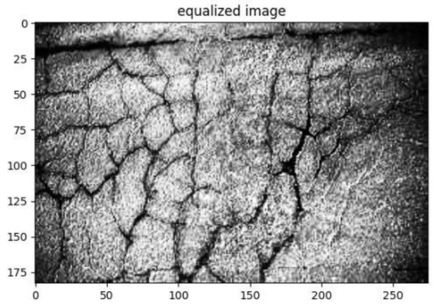
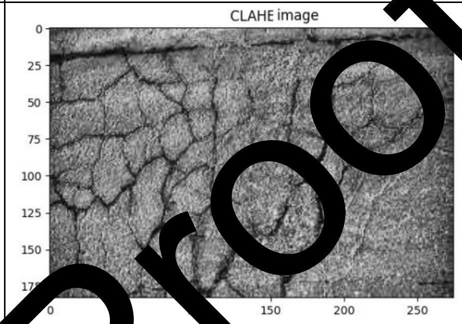
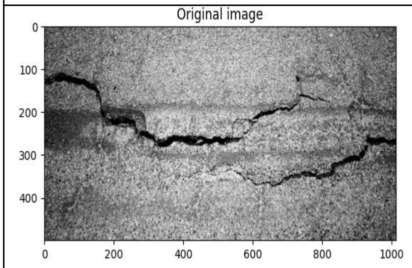
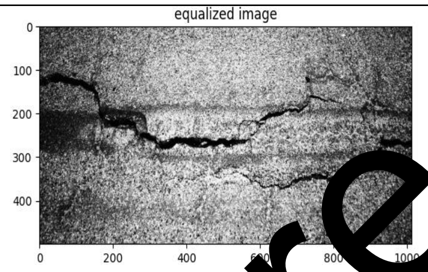
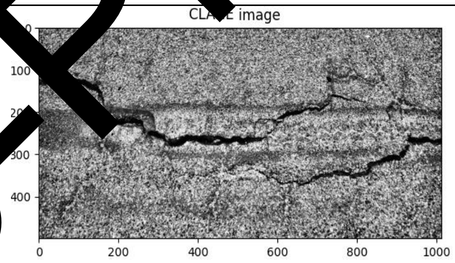
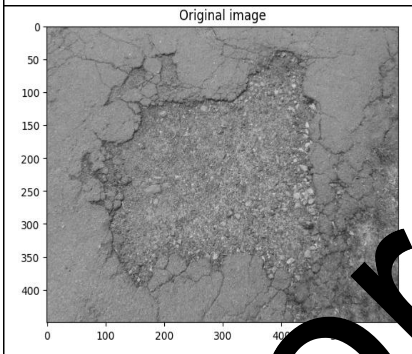
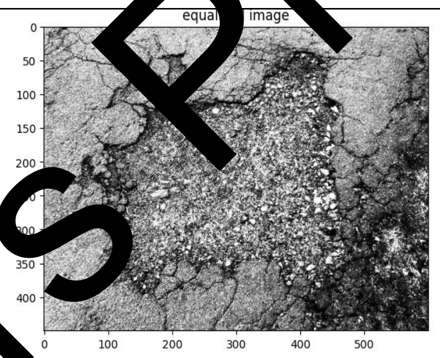
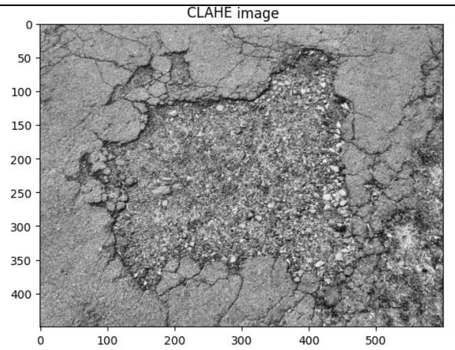
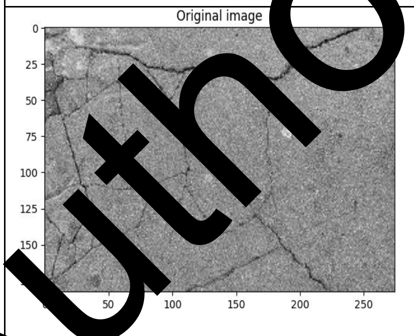
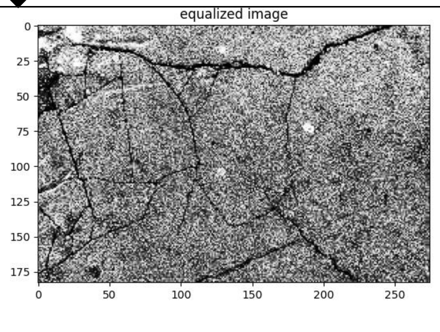
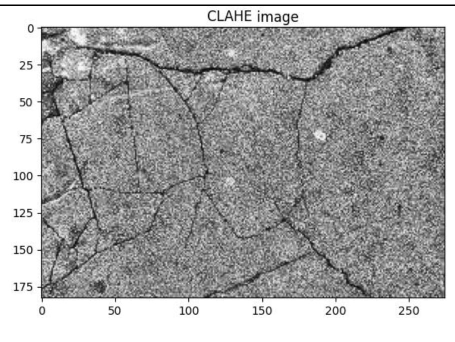
Original Image	**Histogram Equalized Image**	**CLAHE Images**
		
		
		
		

Figure 4: Original, Grey Scaled, and CLAHE Images

b. Performance Evaluation

The performance analysis of the proposed model is calculated based on the correct classification or identification of the cracking image from the testing dataset. We have used traditional performance measures such as Precision (Pr), Recall (Re) and F1 score (F1) which are most commonly used for any classification problems. The performance measures are given in the following Equations.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \rightarrow (1)$$

$$Precision = \frac{TP}{(TP+FP)} \quad \rightarrow (2)$$

$$Recall = \frac{TP}{(TP+FN)} \quad \rightarrow (3)$$

$$F1 - score = \frac{2}{\frac{1}{Precision}+\frac{1}{Recall}} = \frac{2.Precision \times Recall}{Precision+Recall} \quad \rightarrow (4)$$

Here True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are calculated based on the following procedure,

1. **True Positive (TP)**-The proposed method achieved accurate classification or prediction of the cracking images.
2. **True Negative (TN)**-The proposed method accurately classified or predicted the non-cracking images as well.
3. **False Positive (FP)**- the proposed method incorrectly classified or predicted the non-cracking images in the testing dataset, erroneously identifying them as cracking images when they were, in fact, not cracking images. This indicates a misclassification or prediction error in the proposed method for non-cracking images.
4. **False Negative (FN)**- the proposed method provided incorrect classification or predictions for the cracking images in the testing dataset, mistakenly identifying them as non-cracking images when they were, in fact, cracking images. This indicates a misclassification or prediction error in the proposed method for cracking images.

In the evaluation of the proposed method, precision was calculated by determining the number of correctly predicted cracking images out of all predicted cracking images. This metric focuses on the accuracy of positive predictions. On the other hand, recall, also known as sensitivity or true positive rate, was calculated by determining the percentage of correctly predicted cracking images from the total number of actual cracking images. Recall emphasizes the ability of the model to identify all positive instances correctly. The F1 score, which is the harmonic mean of precision and recall, was also calculated. It considers both false positives and false negatives, providing a balanced measure of the model's performance. It takes into account the trade-off between precision and recall and is a valuable metric in evaluating the overall effectiveness of the proposed method. It's important to note that while the F1 score is a useful performance evaluation metric, it is not the sole criterion and other metrics and factors should be considered as well.

c. Performance Analysis

The proposed method for road crack detection on Indian urban roadways was developed by using a Deep Convolutional Neural Network (DCNN) model. To evaluate its performance, the same dataset was used to compare it with existing models in the same domain, such as ResNet, VGG16, and VGG19.The performance evaluation of the proposed method was based on several metrics, including Accuracy, Precision, Recall, and F1 score. These metrics were used to assess the effectiveness of the proposed method compared to the existing models. The accuracy levels of the proposed DCNN method, as well as the existing models (ResNet, VGG16, and VGG19), were plotted and compared. The results analysis indicated that the maximum accuracy was achieved with a higher number of epochs. The figure 8 presented demonstrates the accuracy levels of the proposed method in comparison to the existing models, providing a clear visual representation of their performance.

It is worth noting that accuracy was used as a primary metric for performance evaluation, but the other metrics (Precision, Recall, and F1 score) were also considered to provide a comprehensive assessment of the proposed method. Figure 8 illustrates the calculation of accuracy for the testing phase using equation (1), which takes into account the values of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) from the testing dataset. Similarly, the accuracy values for the ResNet, VGG19, and VGG16 models were calculated using the same test data samples. By calculating accuracy in this manner, the performance of the proposed method is compared with the existing models (ResNet, VGG19, and VGG16) using a standardized metric. This allows for a fair evaluation and comparison of the accuracy achieved by each model on the given test dataset.

Predicated	HE Images		CLAHE Images	
	Actual		Actual	
	Cracking	Non-Cracking	Cracking	Non-Cracking
Cracking	541	09	542	08

$Non - Cracking$	02	148	02	148

Table 2: Proposed DCNN Model

Predicated	HE Images		CLAHE Images	
	Actual		Actual	
	Cracking	Non-Cracking	Cracking	Non-Cracking
$Cracking$	534	16	536	14
$Non - Cracking$	05	145	03	147

Table 3: VGG16 Model

Predicated	HE Images		CLAHE Images	
	Actual		Actual	
	Cracking	Non-Cracking	Cracking	Non-Cracking
$Cracking$	538	12	538	12
$Non - Cracking$	07	143	04	146

Table 4: ResNet Model

Predicated	HE Images		CLAHE Images	
	Actual		Actual	
	Cracking	Non-Cracking	Cracking	Non-Cracking
$Cracking$	537	13	540	10
$Non - Cracking$	0[illegible]	146	02	148

Table 5: VGG19 Model

Model	Precision (%)	Recall (%)	F1 Score (%)	Accuracy (%)
Proposed Model	98.3	99.6	98.4	98.6
ResNet	97	99	97	97.7
VGG16	97.8	98.7	97.2	97.6
VGG19	97.6	99.2	97.5	98.3

Table 6: Performance Evaluation for the HE Images

Model	Precision (%)	Recall (%)	F1 Score (%)	Accuracy (%)
Proposed Model	98.5	99.6	99	98.6

ResNet	97.8	99.2	98.5	97.7
VGG16	97.5	99.4	98.4	97.6
VGG19	98	99.6	98.6	98.3

Table 7: Performance Evaluation for the CLAHE Images

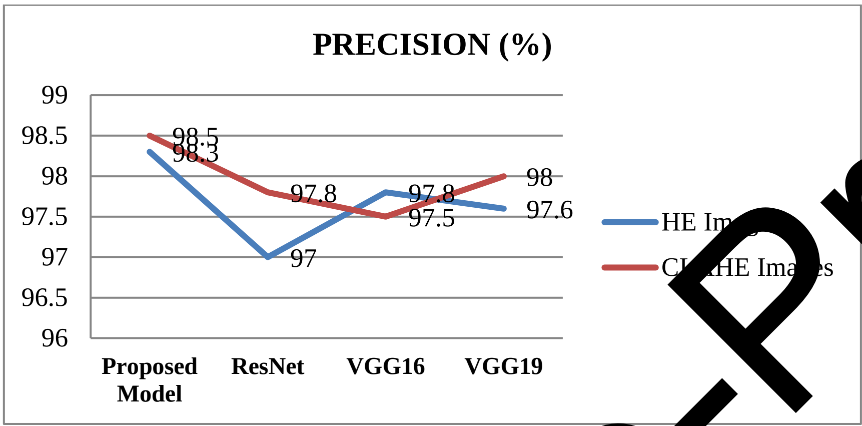


Figure 5: Precision Calculation

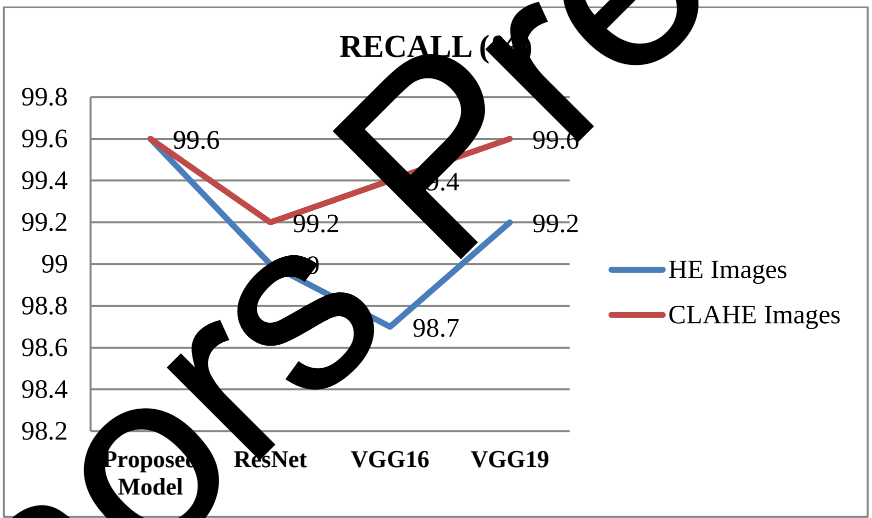


Figure 6: Recall Calculation

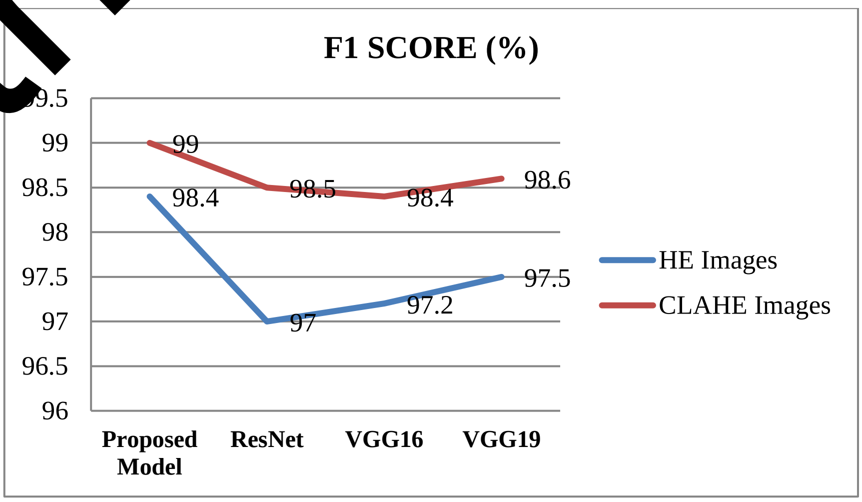


Figure 7: F1 Score Calculation

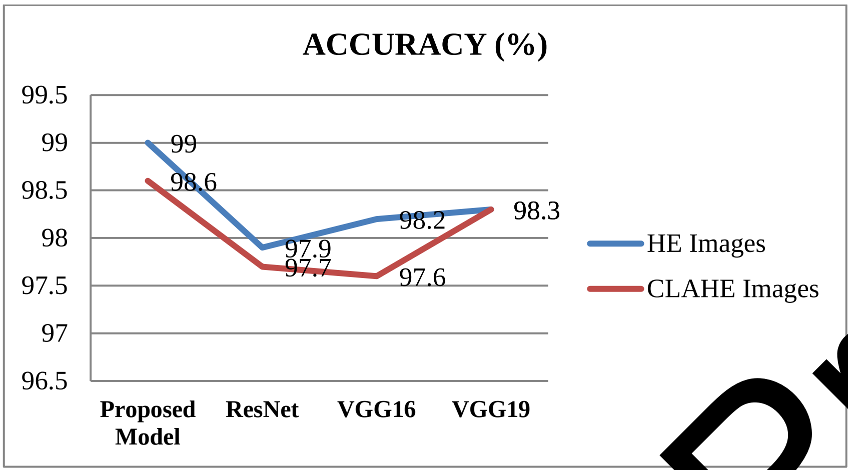


Figure 8: Accuracy Calculation

Table 6 presents the performance evaluation results for the proposed scheme and the existing methods using a shared dataset. The evaluation metrics used include accuracy, precision, recall, and F1 score. The accuracy of the proposed method was measured to be 98.6%, which is very close to the accuracy achieved by the VGG19 method. This indicates that the proposed method performs at a high level of accuracy compared to other models in the same domain. Furthermore, the proposed method achieved impressive results in terms of precision, recall, and F1 score. The precision score was 98.5%, indicating a high proportion of correctly identified positive instances. The recall score was 99.6%, signifying the model's ability to accurately detect a large percentage of the actual positive instances. The F1 score, which considers both precision and recall, was 99%, showcasing the overall effectiveness of the proposed method in identifying road cracks based on the training dataset.

However, it's important to note that the time taken for training and testing was not measured in this evaluation. The performance evaluation primarily focused on the accuracy and related metrics clearly explain in figures 5, 6, 7, and 8.

Conclusion

In this paper, we have presented a model for detecting road cracks on Indian urban roads using a Deep Convolutional Neural Network (DCNN). Based on our literature review, this is the first known initiative focused on road damage detection specifically for urban roadways in India. We collected over 700 images of damaged roads from various urban areas across Tamil Nadu. To enhance image quality and improve crack detection, the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm was applied. The proposed model was trained using a dataset of 5000 images, which included both cracked and non-cracked road surfaces. Each image in the training set was labeled accordingly, and the model was tested using 700 images. The proposed approach consists of two main phases: the first phase involves enhancing the quality of input images using the CLAHE algorithm, and the second phase focuses on training the DCNN model with these enhanced images. Experimental results demonstrate that the model performs effectively in detecting cracks on Indian urban roads. We compared the performance of the proposed model with existing architectures—ResNet, VGG16, and VGG19—using the same dataset. The performance evaluation indicates that our model outperforms the existing ones, achieving accuracy, precision, recall, and F1 scores of 98.6%, 98.5%, 99.6%, and 99%, respectively.

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