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Pavement Surface Condition Rating of Flexible Pavement based on Artificial Intelligence based Deep Learning Technique

Athiappan K
JJ College of Engineering and Technology
Chitra Devi R
Dr.Sivanthi Aditanar College of Engineering
J Naveenkumar
National Institute of Technology
C Makendran
National Institute of Technology
Mehdi Gheisari
mehdi.gheisari61@gmail.com

Shaoxing University
Christian Fernández-Campusano
University of Santiago Chile
Mehidi Esnaashari
K.N.Toosi University of Technology

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Abstract

Developing countries were struggling to maintain its road networks in fit surface conditions due to adherence of the conventional method of evaluating the pavement surface condition using multiple physical equipment. The conventional method to measure the multiple distresses is a time consuming and costlier process. Hence in this research, we propose a deep learning-based Pavement Surface Condition Rating of plastic roads. The proposed hybrid model was adopted to assess the pavement surface condition assessment aligned to Pavement condition rating recommended by IRC 82:2015 used in pavement maintenance of Indian roads. In this research, 4k video image of pavement having distresses such as crack, potholes, patches and raveling are acquired by unmanned aerial vehicle mounted with camera. The collected video dataset was used to develop distress prediction model using YOLOv8 integrated with Gray-Level Co-occurrence Matrix (GLCM) and TAMURA feature extraction algorithm. It is observed from the results that the pavement condition rating based on conventional and deep learning- based Image processing technique has high degree of correlation.

1. Introduction

India is the second largest road network with the length of 6,617,900 km including all types of roads based on classification of construction catering 85% of total passenger traffic and 71% of the total fright traffic. Among the total length, 4,102,000 km roads are surfaced with 2% of concrete pavements and 98% of bituminous pavements[1]. Even though the initial construction cost of bituminous pavement is low but need higher frequency maintenance due to periodic deformation and cracking due to viscoelastic nature of bitumen used adhesive in the bituminous bitumen[2]. With proper maintenance of bituminous pavement, it can sustain its complete life cycle of 20 to 30 years, else the pavement will lose its surface and structural integrity before its life span, nearly within 8 to 12 years[3]. India has constructed the low volume rural roads length of 56,875 km with plastic incorporated bituminous pavement in view of reducing the frequency of maintenance, use of conventional bitumen and environmental impact under PMGSY scheme [4]. India is allocating nearly 1% of overall highway development fund for the highway maintenance. every year. Due to poor pavement maintenance and management, nearly 9,109 fatal accident death on road due to potholes alone in India for the period of 2019 to 2023 period[5]. Most of the roads on India subjected to recurring surface distress due to lack of proper drainage and implementation enforcement on restricting higher axle loads than the standard axle loads permitted[6]. Even though India has standardized the maintenance for roads through IRC and MORTH specification but the adaptation level of maintenance for national highways are higher and very low in case of low volume rural roads due to scarcity of enough fund allotted for the highway maintenance [[7,8]. Nearly 65% of the India total network was shared by the rural low volume roads, lack of proper maintenance will lead to faster deterioration of pavement and poor access to small villages and towns (Vandana Tare 2013, Randhawa et al. 2025). India is relying on convention methods for pavement surface evaluation such as visual condition survey with disadvantage subjective, inconsistent rating and lack of skilled inspector and pavement condition index (PCI) produce constructive evaluation but disadvantage of higher time consuming, scarcity of trained personnel and less cost effective [11]. Meanwhile the image processing technique was adopted for the assessment based on pavement condition Index method by taking the pantographs of various distress are found to be satisfactory [12]. In the current scenario of highway infrastructural development worldwide and in India, the conventional method of pavement surface assessment was unable to meet the demand of completing the pavement surface condition assessment to complete the pavement maintenance paved the need for advanced technique to assess the pavement surface condition [13]. In Egypt, ANN-based distress prediction model for urban roads having various surface distress are developed using various algorithm such as support vector regression, random forest and decision tree, the correlation between the observed and predicted are found to be satisfactory [14]. The performance of ANN and ML model for the prediction of pavements surface condition are compared and found out that the ML based XGBoost produced higher prediction efficiency roughness distress on pavement having thin and thick

overlays[15]. Only the width of cracks and its area on the pavement surface was predicted using image processing technique using deep learning algorithm YOLO v8 algorithm has higher correlation result[16]. The pavement surface polishing was predicted by analyzing the image integrated with ML based Gray Level Co-occurrence Matrix (GLCM) algorithm and showed a promising result to predict the pavement surface texture depth condition [17]. The rut depth was predicted using the image identification algorithm and analytic hierarchy process theory, the developed model was able to predict the rut depth of with an accuracy of 0.7 [18]. AI based deepening learning assessment of the pavement condition based on the laser captured image has higher reliability but it need highly trained technical person and the seeped of data acquisition is found to be slower rate and costlier [19]. It was unable to conduct reliable AI based distress assessment due to scarcity of open-source data related to the pavement surface distress assessment on the pavement [20]. From the above literature survey, it was found out that the conventional method of pavement condition rating was time consuming, costlier and not able to meet the current pavement condition assessment. Various AI-based pavement condition assessment are only available for the foreign roads which was constructed with pavement construction material with varied physical properties and environment while comparing to the India and most of the research are based on Pavement Condition Index (PCI) which uses a scale of 1 to 100 [21]. No AI-based research are available related to Indian context using Pavement Condition Rating (PCR) used for the pavement surface condition assessment which uses a scale of 1 to 3 according to IRC 82 2015. To overcome this issue, we proposed a deep learning-based pavement surface condition rating of plastic roads on south Indian roads in this research work.

2. Methodology

In this research, the flexible pavement distress is determined based on the conventional method recommended by the IRC 82: 2015 and compared with the prediction model developed based on deep learning-based image processing technique. The study area selected for this research are 2000m length of plastic road constructed in Madurai corporation limit. Madurai, Tamil Nadu, India. The age of road was found to be 9 years and falls under traffic condition of low volume roads according to IRC 37: 2018 classification. In the conventional method of pavement surface evaluation, the distress such as cracking, potholes, ravelling and patches found on the above study area was determined using the manual measuring equipment tape to compute the area of distress and converted to weighted rating value for each distress. Each weighted rating value was summed to get final rating value and the condition of pavement is determined. In the artificial Intelligence based image processing technique, the video image acquisition of the entire road stretch considered for study was captured using the UAV (drones) fitted with high resolution camera. The data collected as video image was pre-processed and subjected to develop deep- learning model used to classify the pavement surface defects cracks, patches, potholes and ravelling. The results from the manual methods and image processing technique are compared and validated for the real time usage. The schematic representation of methodology used in this research was shown in Fig. 1.

3. Pavement Surface Condition Rating by Conventional method

The rating and conditions of the corresponding distress found in the study stretch such as cracking, ravelling, potholes and patches are determined by area of each distress with respect to total area of the pavement under surface condition evaluation by manual methods using the corresponding appropriate equipment's. The irregular area distress was calculated using the Simpson rule. The ratings and conditions of each distress range with respect to range of individual distress according to IRC 82-2015 are given in Table 1. The multiplying factor used for the individual distress for calculating weighted rating value according to the IRC 82:2015 was given in the Table 2. The type of distress found on the study stretch was shown in Fig. 1. The estimated ratings and conditions of induvial distress and overall condition of pavement considered for research are shown in Table 3. From the table the overall rating and condition of the study stretch (pavement) was found to be 1.765 and fair condition respectively.

Table 1
Pavement Condition and rating based on range of individual distress according to IRC 82-2015

Types of distress or Defects	Range of Distress or defects		
Cracking%	> 15	5–15	< 5
Ravelling%	> 10	5–10	< 5
Potholes%	> 0.5	> 0 and <_0.5	NIL(0)
Patching%	> 10	1–10	< 1
Rating	1	1.1-2	2.1-3
Conditions	Poor	Fair	Good

Table 2
Multiplying factor for calculating Weighted Rating Value Table according to IRC 82-2015

S.No	Pavement distress or defects	Multiplier factor
1.	Cracking	1.0
2.	Patches	0.75
3	Potholes	0.5
4.	Ravelling	0.75

Table 3
Estimated ratings and conditions of individual distress and overall condition of pavement considered for study

Land Mark	Total length measured (m)	Types of distress found	Area of distress(m^2)	PCI density (%)	Rating based on IRC 82:2015	Condition (based on IRC 82:2015)
Main parking	400	Patches	40.430	1.55	1.2	Fair
		Potholes	1.687	0.06	1.1	Fair
B -halls	450	Patches	8.244	2.11	1.3	Fair
		Potholes	0.636	0.162	1.1	Fair
Back gate to arch dept	301	Patches	12.818	1.216	1.2	Fair
		Potholes	2.545	0.241	1.3	Fair
Back gate to front gate	840	Patches	18.085	2.15	1.3	Fair
		Potholes	3.986	0.474	1.8	Fair
		Cracks	0.722	0.8	3	Good
		Ravelling	13.88	1.65	2.9	Good

Table 4
Estimated Rating of study stretches (pavement) based on percentage of overall distress

Distress type	Percentage of distress (%)	Rating of Individual distress	Multiplying factor	Weighted rating value
Cracking	0.8	3	1.0	3.0
Patches	7.026	1.7	0.75	1.275
Potholes	0.937	1.2	0.5	0.6
Ravelling	1.65	2.9	0.75	2.175
Final Rating Value				1.765
Condition				Fair

4. Deep Learning-based pavement condition rating

The deep learning-based approach was proposed to detect the pavement surface defects. An unmanned aerial vehicle with high-resolution camera was used to acquire the high-quality 4k video image of the pavement surface. The designed hardware setup can works optimal under any weather conditions i.e. upto 50^{o}C and 85% humidity. The 4k video was then preprocessed by splitting into individual image frames subjected to annotation and augmentation process. The main intention of this phase is to filter out the blur images, resize each of the images to 640x640 so as to support the deep learning models and also to reduce the computation time involved in the training period. In addition, the brightness of the image was improved to get better visibility on the distress. The processing carried out in this stage helps the models to learn effectively, and thereby save time with clean and balanced data.

The core part of this proposed work is to use the hybrid model for the pavement condition analysis. The YOLOv8 was used to extract the deep visual features of the pavement, GLCM detects the surface irregularities and Tamura algorithm extracts the textual features. GLCM is used for the texture analysis of the dataset based on pixel density in the greyscale images. GLCM identifies the pavement surface defects based on statistical features of dataset (images) such as contrast, correlation, energy reflected, dissimilarity and entropy of the image. TAMURA feature extraction mimics the human texture perception that has the ability to detect the pavement surface irregularities. It classifies the defects based on the following parameters such as coarseness, contrast, directionality, line-likeness, regularity and roughness. The texture features extracted from GLCM and Tamura methods are combined into a comprehensive feature vector for each road surface image. YOLOv8 architecture consist of backbone network, model neck and detection head. The essential features from the input images are extracted using the model C2fbackbone structure. The features extracted by the backbone using multiple layers are refined and enhanced at the model neck using path aggregation network used to detect small pavement surface defects like cracks. The detection head is used to predict the bounding box, various defect label and confidence scores and aids in detect the pavement surface defects with high accuracy. Finally, the user interface was implemented to depict the surface defects on the pavement by using pavement condition rating according to IRC 82-2015.

4.1 Dataset Collection and Pre-processing

The dataset of the entire study stretch was collected using the unmanned aerial vehicle (UAV) fitted with the high-resolution video camera with capability of capturing video frame of 4k (7680 X 4320 pixels) at the rate of 60 frames per second having a video format of MOV (H.264/MPEG-4 compression). The UAV can operate at a temperature of 0ºC to 50ºC up to 85% of humidity. It is bundled with AF-P DX NIKKOR 18-55mm f/3.5-5.6G VR lens. The datasets were collected in different lighting, environmental factors such as different temperature, angles, distances and illuminance

(from morning 7am to evening 5pm at an interval of 1 hour). The data pre-processing involves converting the obtained image into standardized image of 640X640 pixels compatible to computer vision model YOLOv8. It detects the defects in the pavement surface by breaking the video into individual done by image frame. The redundant or blurry frames are removed to avoid duplication followed by improving contrast, brightness, and sharpness and annotation prepared using Roboflow. The annotated images are subjected to the different types of image augmentation such as geometric transformation, photometric transformation, noise-based augmentation. To ensure accurate localization of defects, correct label alignment and reliable training data, the bounding boxes of annotated image box are automatically adjusted to match the transformed images. The annotated images with defects and without defects are shown in Fig. 3a & 3b respectively.

4.2 Classification and Labelling of Dataset

The dataset collected were divided into three categories of usage, 70 percentage used for model training, 20 percentage used for model validation and 10 percentage of data used for the model testing. The data used for the CNN training model are classified into multiple classes. The positive class image represents the image with road surface defects (potholes, patches, ravelling and cracks) and negative class image represents the road without surface defects. The 70% of the image dataset was used to train the CNN model for learning the presence and absence of defects. The trained model is used to predict the presence and absence of defects in new or unseen images that are shown in Fig. 4 and Fig. 5 respectively. The multiple class dataset includes images of four different types of defects such as cracks, patches, potholes and ravelling that are observed in this research.

4.3 Pavement Surface Defect - Model Training

The YOLOv8 architecture was initialized and trained with 50 epochs where 8 images per batch were considered to avoid underfitting and memorizing the training data. The multiclass classification was done using cross-entropy loss, bounding box regression loss and abjectness or confidence loss. The Adaptive Moment Estimation (ADAM) uses momentum-based optimization and adaptive learning rates for optimizing the model parameters consisting of various sensitivities and gradient magnitudes. The training parameters such as training loss, validation loss, precision, recall, and mean Average Precision (mAP) are used to monitor the efficiency and accuracy of the training process. The trained images and the training results are shown in Fig. 6 and Fig. 7 respectively.

4.4 Pavement Surface Defect - Model Validation

The Pavement Surface Defect Model developed using the deep learning network was validated using the 10% of random images from the dataset that was not utilized for training. The pavement surface defects (Potholes, patches, cracking and ravelling) are provided as input and the pavement surface defects detection ability was assessed as shown in Fig. 8. The validation results observed for the proposed model has a precision of 72.3%, recall score of 68.1%. The confusion matrix for the true and predicted pavement surface defects are shown in Fig. 9. The precision confidence curve value varies from 1.0 to 0.658 as shown in Fig. 10.

5. Comparative Analysis

The comparison of pavement rating obtained from the conventional method and their results are compared against the deep learning-based image processing techniques. The results are depicted in the Table 5. The variation of area for different pavement surface distress (potholes, cracking, ravelling and patches) obtained by conventional methods varies with the distress identified through deep learning-based image processing techniques. Figure 11 depicts the variation of various distress types by conventional and AI based image processing technique. Even though pavement surface detection model developed by deep learning based image processing technique has a confidence level of 1 to 0.58, the final rating value according to IRC 82: 2015 has slight variation between the conventional method and AI based

image processing technique found to be 1.765 and 1.73 falls under fair condition. The huge variation of area was found for the area of potholes and ravelling detected by these two methods, whereas the area of cracking and patches detected shows less variation by both the methods.

Table 5
Comparative analysis of pavement rating obtained between the conventional method and deep learning-based image processing techniques

Distress type	Percentage of distress by conventional method (%)	Percentage of distress by AI based image processing technique (%)	Rating of Individual distress by conventional method	Rating of Individual distress by AI based image processing technique	Multiplying factor	Weighted rating value for conventional method	Weighted rating value by deep learning technique
Cracking	0.8	1.15	3	3	1.0	3.0	3.0
Patches	7.026	6.52	1.7	1.7	0.75	1.275	1.275
Potholes	0.48	1.73	1.2	1.0	0.5	0.6	0.5
Ravelling	1.65	4.23	2.9	2.9	0.75	2.175	2.175
Final Rating Value						**1.765**	**1.73**
Condition						**Fair**	**Fair**

6. Conclusion

The pavement surface condition ratings value obtained based on the conventional and deep learning (DL)-based image processing techniques. For both the cases, the condition rating is found to be fair. Hence this DL-based model can be used for evaluating the pavement surface condition of roads constructed in south India using similar specification. The variation of distress estimated for the cracks and patches based on the conventional method and DL-based image processing techniques have high degree of correlation, whereas the other two distress potholes and ravelling found to have less degree of correlation.

The proposed hybrid model is found to process large quantity of data necessary for modelling with higher accuracy, and have faster rate of data processing. This research work carried out is only suitable to evaluate the pavement surface conditions of the plastic roads. The study is made only on the following distress such as crack, potholes, ravelling and patches, hence the proposed model is limited to predict the mentioned distress alone. Similarly, the model is valid only in the southern Indian road conditions which reflect the bitumen material characteristics supporting the hot climatic conditions. The research can be extended to consider all types of pavement surface distress and roads all over the India with all climatic conditions and various material characteristics.

Declarations

Author Contribution

A. wrote the manuscriptR.J.Modelling workC.Supervision of WorkR.Figure preparationEsnaashari . Grammer checkFernández-Campusano. Supervision

Data Availability

The datasets generated and analyzed during the current study are not publicly available due but are available from the corresponding author on reasonable request.

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Figures



Figure 1

Distress found on the study stretches

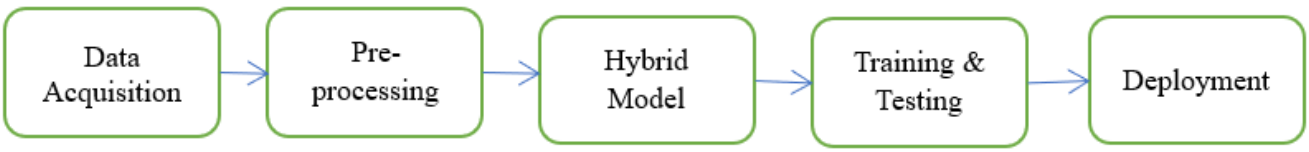


Figure 2

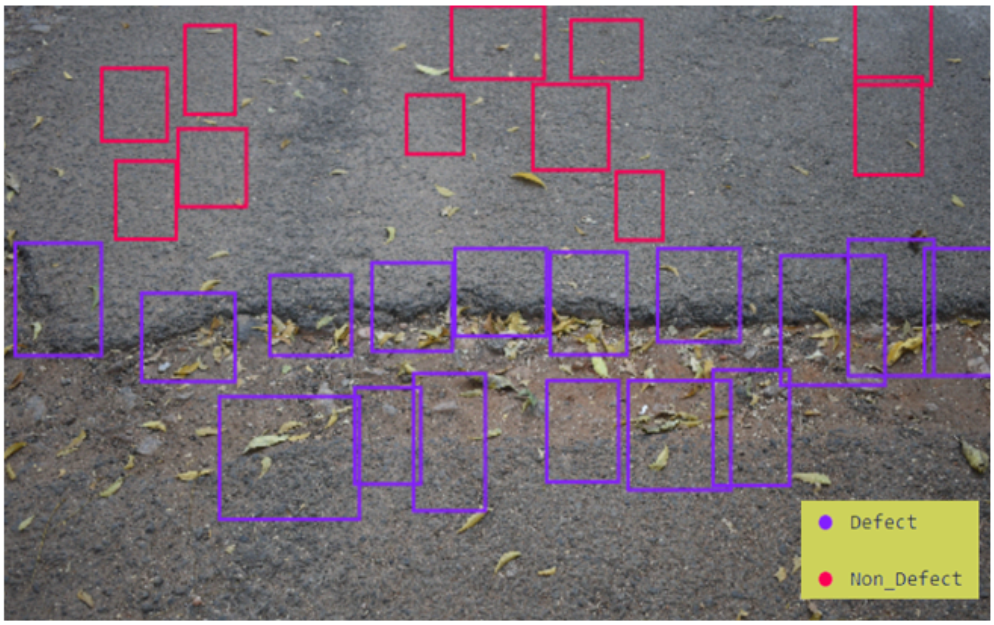


Fig. 3(a)

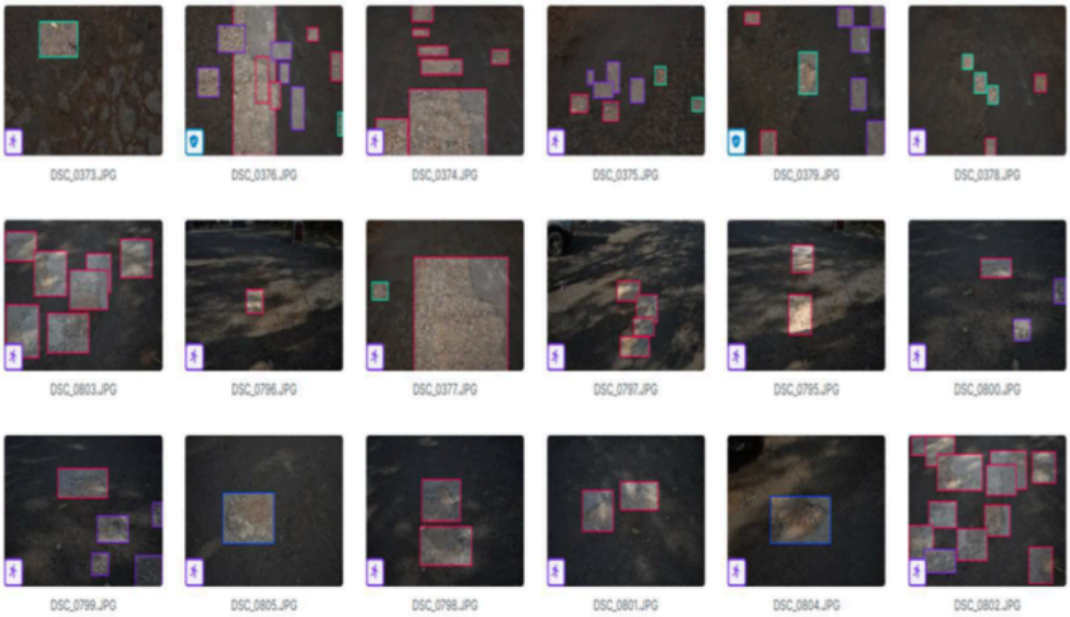


Fig. 3(b)

Figure 3

(a). Annotated Image with and without defects

(b). Annotated Image with various defects (Potholes, patches, cracks and ravelling)

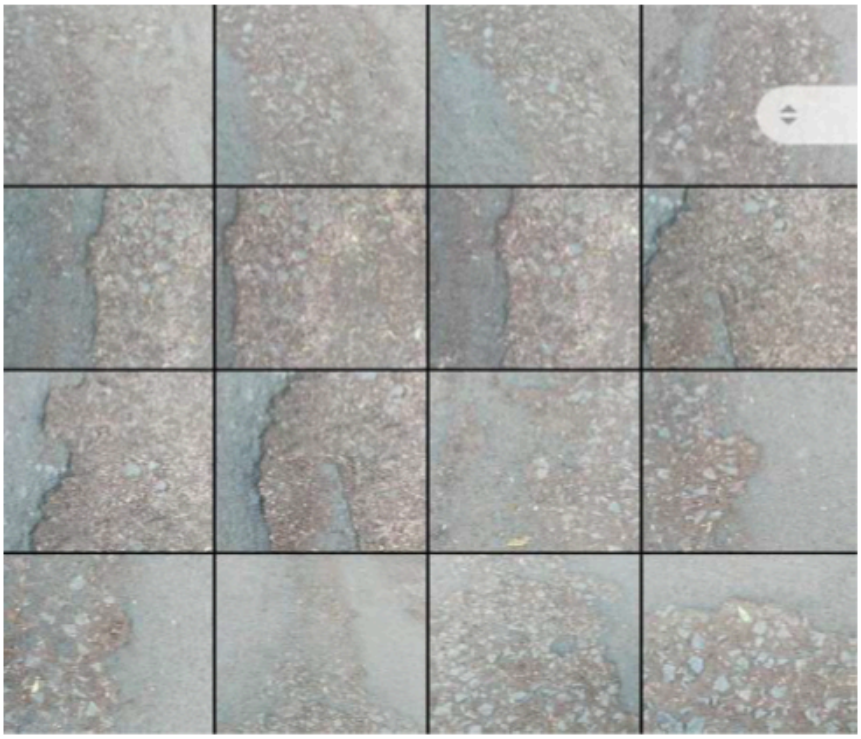


Figure 4

Positive image having road surface defects

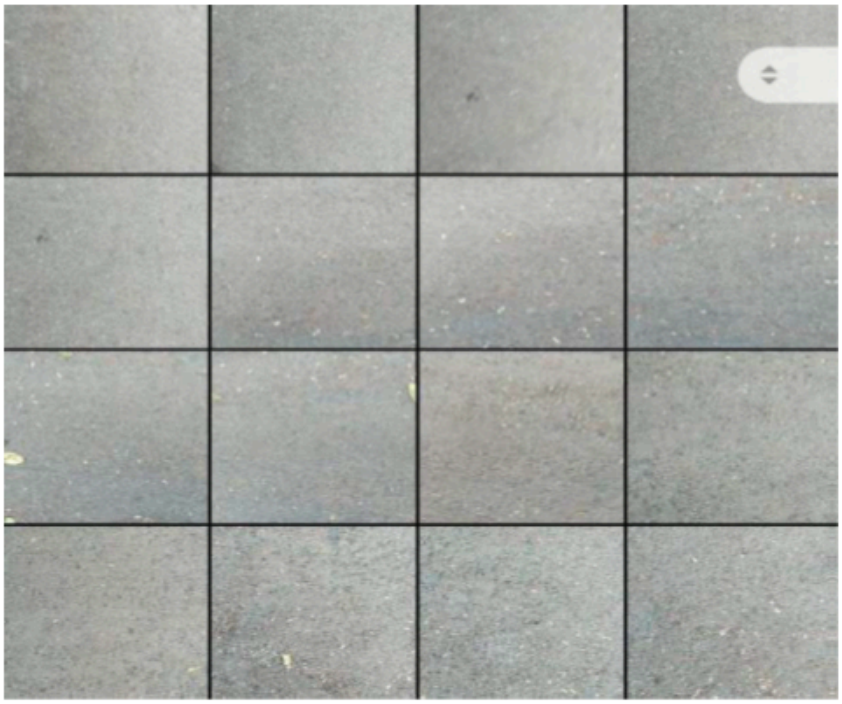


Figure 5

Negative image without road surface defects

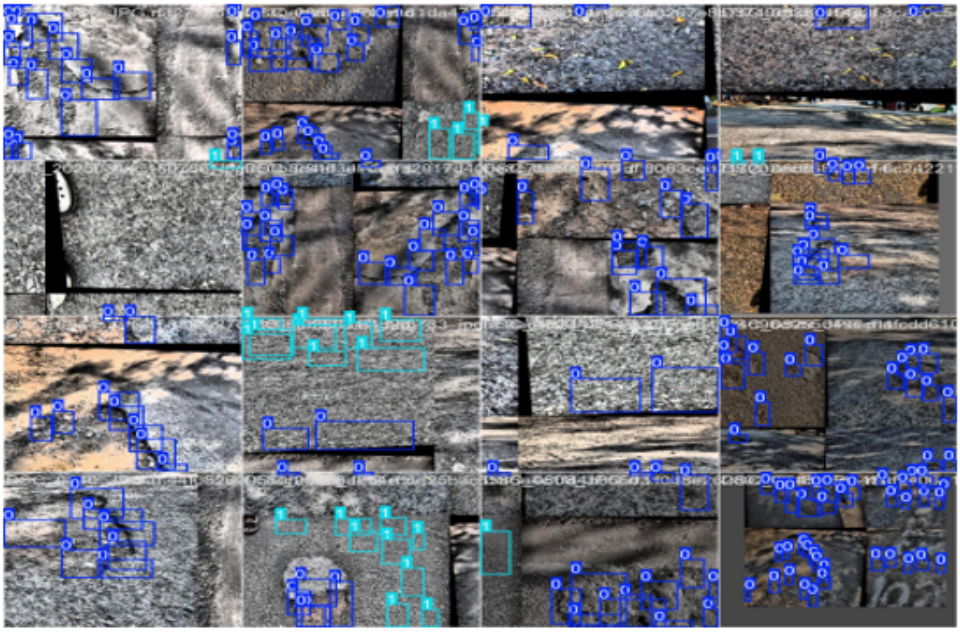


Figure 6

Images Pavement Surface defects used for training

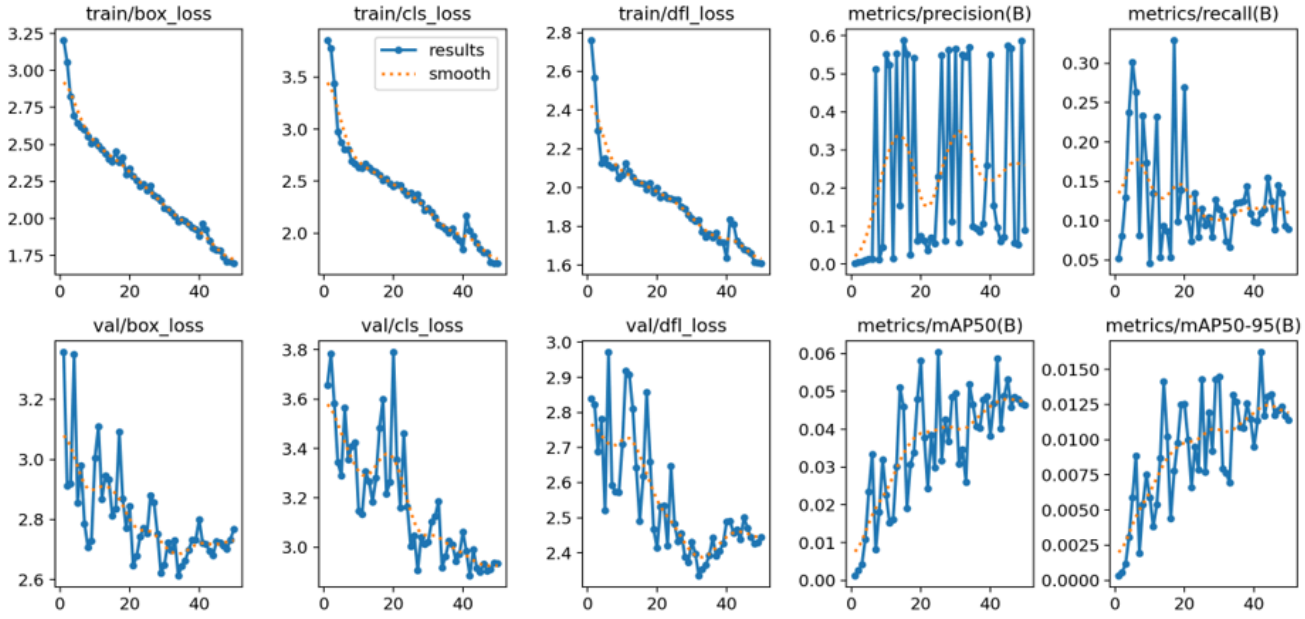


Figure 7

Pavement surface defects training results



Figure 8

Surface defects Validated image a) patches b) potholes

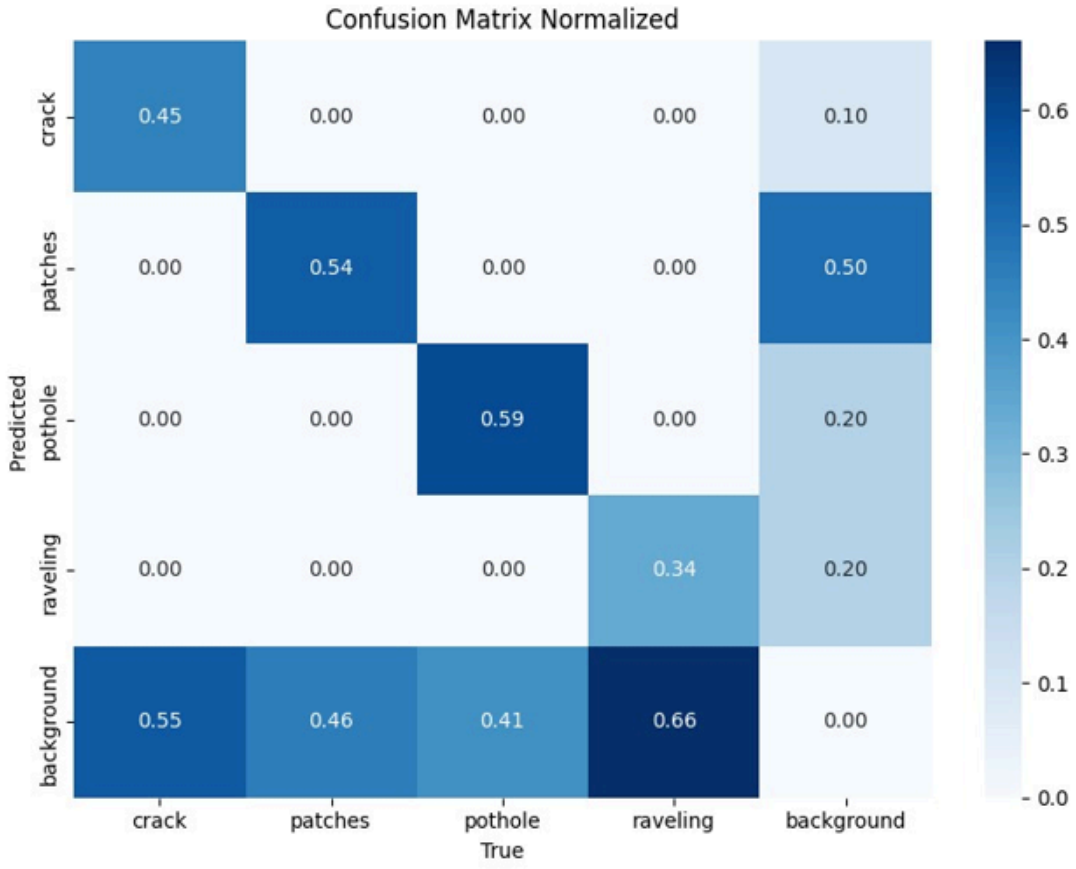


Figure 9

Confusion matrix for true and predicted multiclass surface defects

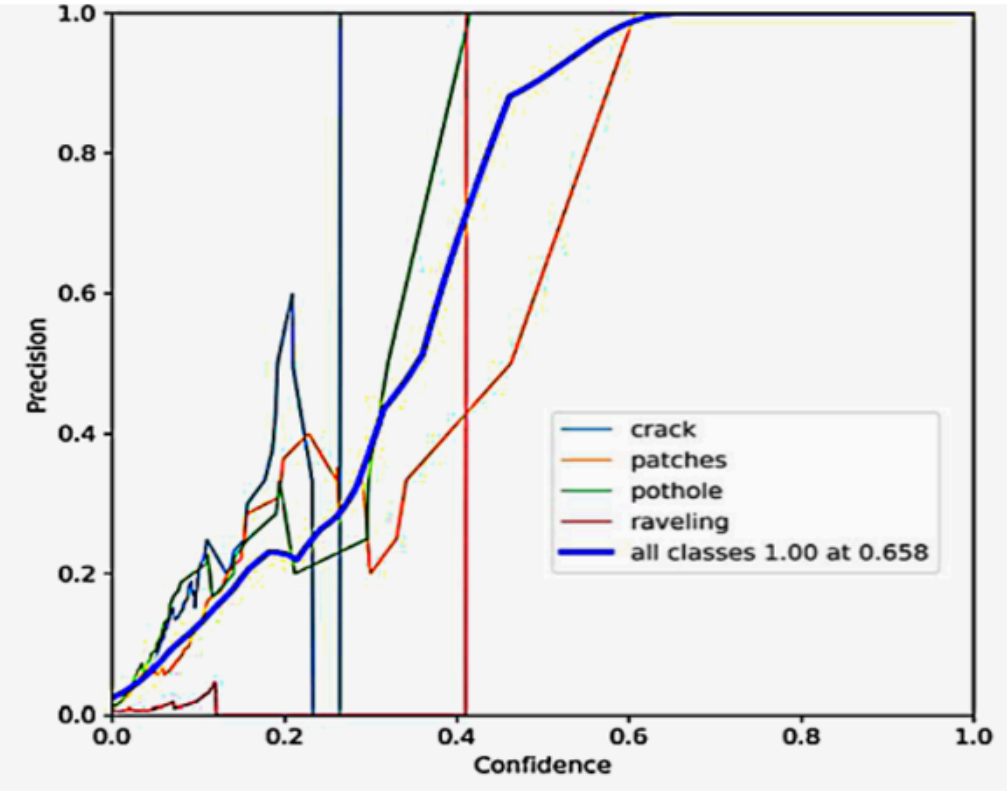


Figure 10

Pavement Surface defects precision- confidence curve

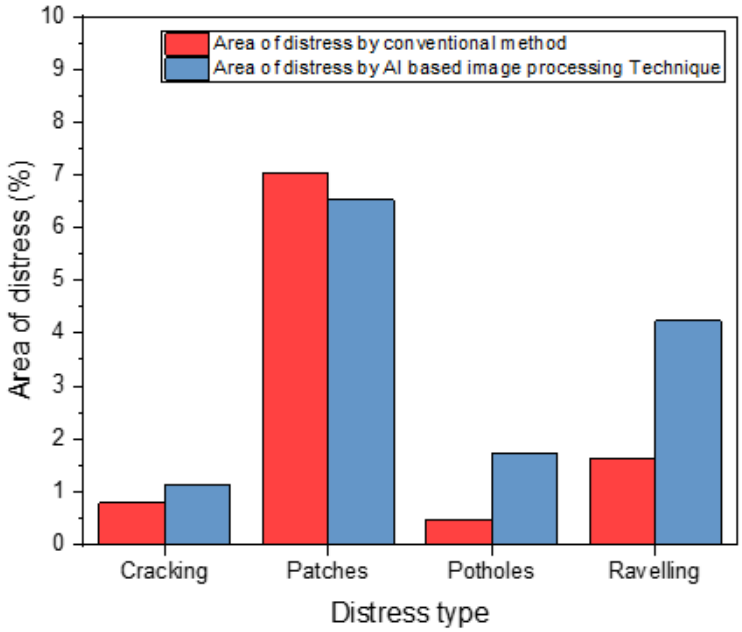


Figure 11

Percentage variation of various distress types by conventional and AI based image processing technique