CHAPTER 26

Automated Pavement Distress Detection using YOLOv8 with Augmentation Techniques

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ABSTRACT

Roadways are pivotal in transportation infrastructure, serving as essential pathways for travel and connectivity. Well-maintained highways significantly contribute to a nation's economic growth. Highways are essentially pavement structures with three to four layers designed to provide structural strength and endure repetitive traffic loads. However, over time, the continuous impact of heavy traffic and adverse weather conditions leads to a gradual loss of structural integrity. This deterioration results in various distresses on the pavement surface, such as cracks, potholes, and ravelling. The durability and functionality of pavements are critical to ensuring safe and efficient transportation. This study focuses on implementing artificial intelligence to enhance the assessment of pavement conditions, addressing limitations in traditional manual methods. This research employs Convolutional Neural Networks (CNN) and the You Only Look Once (YOLO) model to detect, classify, and quantify pavement distresses such as cracks, potholes, and rutting, by training it on the open-source database which has around 14,000 images. The YOLOv8 architecture was selected for its superior performance in object detection tasks. The models were evaluated using metrics like Mean Average Precision (mAP), precision, and recall, achieving promising results for certain distress types. From the results, it was observed that the YOLOv8 model gives around 25% precision and after the data augmentation, the results improved to 37%. Also from this trained model, the website developed for automated pavement distress detection using video. The findings demonstrate the potential of AI-driven approaches to automate pavement condition assessments while highlighting challenges, including dataset imbalances and variability in distress detection accuracy.

Keywords: Pavement distress; Deep learning; Convolutional Neural Network (CNN); YOLOv8; Pavement Condition Index (PCI).

1.0 Introduction

For connecting villages, cities, districts, states, production lines, and even countries, roads are considered one of the most important elements in civilized communities (Shatnawi, 2018).

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Roads or Pavement is a smooth finished surface, which helps it be durable and should withstand the designed traffic and other environmental conditions, for a life span of 20-30 years. A pavement is a structure, whose primary function is to distribute the designed traffic loads among the pavement layers. Due to material deterioration brought on by excessive traffic, unfavourable weather, aging, or improper maintenance, pavement loses its structural strength (Jianqing WU, 2022; Walaa *et al.*, 2019) Improving the structural strength of pavement, will increase riding quality and enhance travellers' comfort levels, so for improving structural strength there is a need for pavement distress data (Deluka-Tibljaš *et al.*, 2013). Still, the timely detection of distress and the application of appropriate treatment methods are most important for treating the pavement (Chan *et al.*, 2011). Researchers and transportation agencies are attracted by the importance of a timely manner of detecting distress and so many researchers have started working on pavement inspection technologies, which can accurately assess pavement distress and its severity (Zhu *et al.*, 2022).

Pavement functional evaluation is used to evaluate the condition but is mostly done by manual method and visual observation to identify the pavement distress and its severity, based on which Pavement Condition Index (PCI) is calculated. Based on the calculated PCI value, road condition was graded from poor to good, and according to IRC:82 for Indian conditions and ASTMD:6433 as international standards treatment methods are suggested for repairing roads. Moreover, while conducting manual inspection tasks, there exists the potential for human visual mistakes, as well as safety concerns due to the proximity of passing motor vehicles.

Additionally, these operations have the potential to disrupt the flow of traffic. To overcome the limitation of manual methods for evaluating conditions, there is a need for automated distress detection method, which can be used to create to assess, track, and chart the progression of both the surface and subsurface structure of the pavement, along with the profile of any distress. In an endeavor to reduce expenses and expedite maintenance activities, transportation departments are emphasizing the advancement of automated profiling systems for evaluating pavement distress. While automated data collection methods offer numerous advantages, they also result in a substantial volume of raw pavement data. Analyzing and making decisions based on this raw data necessitates the expertise of human professionals.

From literature review, it was observed that most of research is focused on crack and pothole type of distress, but for calculating PCI value, other type of distress data and its severity is needed. So, this research mostly focuses on identifying the distress type from images, where the training of model will be done on the open-source datasets and based on that distress identification of raw images which are collected from the field, will be done using trained model and based on the condition of pavement will be evaluated.

2.0 Literature Review

For knowing the potential research gap, a comprehensive literature review was performed to know how the researchers are using machine learning for the detection of distress

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in pavements, and which extra techniques need to be employed for extracting the features from images. (Astor *et al.*, 2022) used Agisoft Metashape Professional Software and Build Dense Cloud process for obtaining a 3-Dimensional (3D) model, from which the type and dimensions of the image are observed. For this 2388 photos were captured using drones and processed for producing an orthophoto as a 3D model. The observed results were validated with actual field measurements. From the study, it was observed that when the obtained depth of pavement obtained compared with the real figures, it was obtained as 0.3 to 3 cm. (Shatnawi, 2018) detects the cracks in place north of Jordan through four processes namely Image Enhancement and Pre-processing, Feature Extraction, Neural Network Modelling, and Validation. For this researcher used 800 images which include cracked and crack-free pavement by cropping the original image. For the detection of distress, ANN modelling was used with variable learning backpropagation function to train the network. The method detected distress with 90% Sensitivity, 60% Specificity, 82.5% Accuracy, and 87% Precision.

(Pauly *et al.*, 2017) concluded that a deeper CNN network would provide a better result for pavement crack detection. CNN was developed using Keras by TensorFlow as a backend, which consists of four convolutional, pooling layers and two connected layers. From the results, it was observed that it detects successfully pavement distress, but fails for the new locations. (Walaa *et al.*, 2019) used the MATLAB toolbox CrackIT and DeepCNN approach for pavement distress detection in Massachusetts. Unmanned Aerial Systems (UAS) with thermal and visual cameras are used for the collection of images for predicting pavement distress. From the study, it was found that CrackIT was found inaccurate, and also some false detections were observed.

Single Shot Detector (SSD) MobileNetVI network was found accurate for distress prediction and for determining the width of cracks, the U-Net model was used. Crack 5000 database and other various open-source datasets were used for enhancing the performance of the model and which will lead to better detection of distress. (Ali *et al.*, 2019) for detecting cracks proposed a CNN model for which a dataset of 4000 patches was created using images captured from various road sections in the UAE. For the detection and localization of cracks, the sliding window technique is combined with the CNN model. With different epochs of training, it was observed that the 20th epoch had the greatest training and validation accuracy, 92% and 90%, respectively.

From the literature review, it was observed that most researchers have used machine learning models for the identification of distress and image processing techniques for distress feature identification from images and around 500 to 28000 images were used for training with the pixel size of 900x1000 to 150x150, also maximum the sample size for training more will be the accuracy. For measuring performance of models, researchers have calculated recall, True Positive Rate (TPR), Precision, Mean Average Precision (MAP), F1 Score, Mean Intersection Over Union (MioU) and Accuracy. Studies have made use of different neural networks and different image processing processes for distress feature identification as presented in Table 1.

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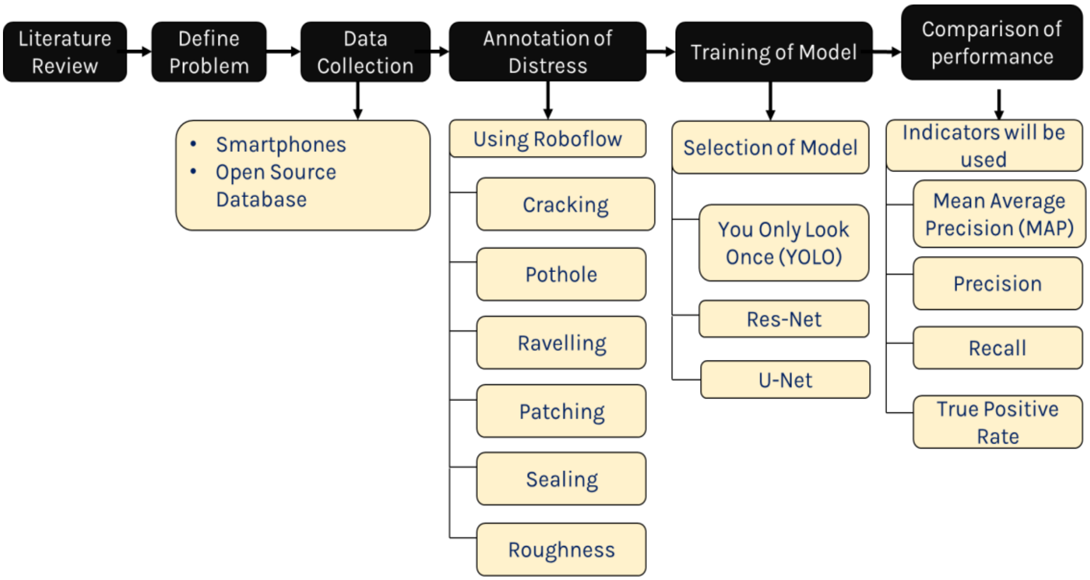
Table 1: Summary of Literature Review

Sr. No.	Type of Distress	Data Collection Method	Feature Identification Method	Network for Detection
1	Cracking	• Thermal & Visual Cameras (Ranyal *et al.*, 2022) • Open Source • Microsoft Kinect (Zhang *et al.*, 2018) • BaidueMap (Lei *et al.*, 2020) • UAV Images (Outay *et al.*, 2020; Romero-Chambi *et al.*, 2020; Shaghlil & Khalafallah, 2018) • Drone Video (Astor *et al.*, 2022) • CCD Cameras (Zhou *et al.*, 2022)	• Image Processing (Liu *et al.*, 2021; Zakeri *et al.*, 2017) • Colour Image Processing • Image Thresholding • Image Smoothing • Image Denoising • Feature Extraction Filter Kinect Algorithm (Zhang *et al.*, 2018)	• SSDMobileNet (Qurishee, 2019) • U-Net (Li *et al.*, 2021) • AlexNet (Li & Zhao, 2019) • GoogleNet (Tang *et al.*, 2021) • SqueezeNet • ResNet (Li *et al.*, 2021; Samma *et al.*, 2021) • DenseNet (Ranjbar *et al.*, 2021) • YOLO (Majidifard *et al.*, 2020; Zhu *et al.*, 2022) • CNN (Abdeljaber *et al.*, 2018; Ali *et al.*, 2019) • Random Forest (Pan *et al.*, 2018)
2	Pothole	• UAV images (Outay et al., 2020; Romero-Chambi et al., 2020; Shaghlil & Khalafallah, 2018) • BaidueMap (Lei et al., 2020)	• Conversion into 3D • The same Image Processing Method was Used as above.	• YOLO (Lei et al., 2020) • Random Forest (Pan et al., 2017) • Faster R-CNN (Wang et al., 2019)
3	Patching	• UAV Images (Outay et al., 2020; Romero-Chambi et al., 2020; Shaghlil & Khalafallah, 2018) • BaidueMap (Lei et al., 2020)	The same Image Processing Method was Used as above.	• YOLO (Lei et al., 2020)
4	Rutting	• UAV Images (Outay et al., 2020; Romero-Chambi et al., 2020; Shaghlil & Khalafallah, 2018)	Digital Elevation Method	

3.0 Methodology

For Data Collection, pavement images can be captured using UAV cameras, Smartphone cameras, or using open-source databases of pavement images.

Figure 1: Methodology Followed



After data collection, Convolutional Neural Network (CNN) model is made for the detection and classification of distress. After classification, Image processing techniques like Standardization of Images, Image Enhancement, Colour Image Processing, Image Denoising, Image Thresholding, Morphological Processing, and others can be used for distress identification. After the identification of distresses, for quantification of distresses each distress dimension needs to be measured & by that the severity level of distresses to be measured according to ASTMD6433.

The methodology discussed for determining severity level was followed earlier, but quantifying distress dimensions pixels per metric value is needed, which is a challenging task, and also this CNN model can only detect one type of distress from one image. So, for the detection of multiple distress in one image, we used the YOLO model and by using this model, quantifying the distress severity with help of the image processing process is eliminated.

Reframed Methodology is like a collection of data (pavement images), categorization of distress and its severity using the YOLO model, and then calculating PCI values, which is presented in Figure 1. The function of the YOLO model like training and testing of images is explained in the section. By knowing the severity level, for each distress type Pavement Condition Index (PCI) value is measured and the total PCI value is calculated for the whole pavement section. Based on PCI value, the overall condition of the pavement section can be known, and based on that appropriate treatment method can be recommended.

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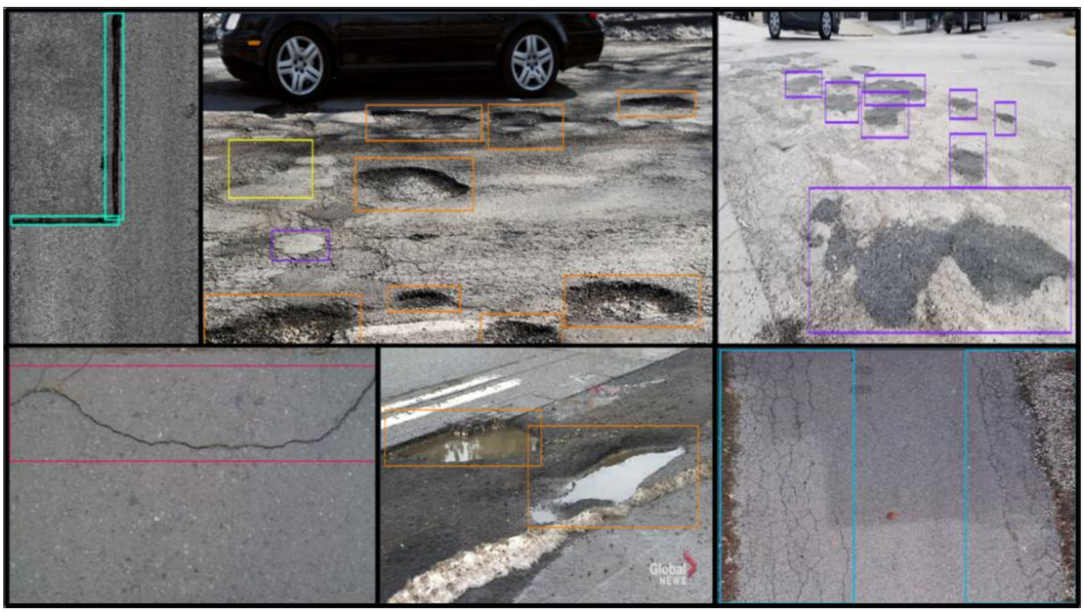
4.0 Model Analysis and Results

For model training, 14,953 total images were collected from the open-source database, which was distributed into the training set, validation set, and test set with a percentage of 75%, 15%, and 10% respectively. The object's class number and the locations of the bounding box's edges are labelled on each image. With an average of 1.1 annotated objects per image, 17,182 annotations overall, and a median image ratio of 1280x1080, an image may contain several objects and classes. Auto-orientation pre-processing was used in the photos; no augmentations were used. Dataset represents different types of distresses like Cracking (5614), Alligator Cracking (4464), Pothole (2660), Sealing (1331), Shoving (1069), Patching (921), and Ravelling (568), suffering from a class imbalance. The model was trained on a dataset focused on identifying various pavement distress types, such as alligator cracking, potholes, patching, and other related issues. The dataset was split into three parts:

- *Training Set:* 11,215 images, used to train the model by adjusting weights through backpropagation and minimizing the loss functions.
- *Validation Set:* 2,243 images, used to tune model hyperparameters and prevent overfitting by monitoring performance on unseen data during training.
- *Test Set:* 1,495 images, used to evaluate the model's effectiveness on new, unseen data after training.

Figure 2: Annotated Images: Cracking (Red), Alligator (SkyBlue), Pothole (Orange), Patching (Violet), Ravelling (Yellow), Sealing (Light Green)



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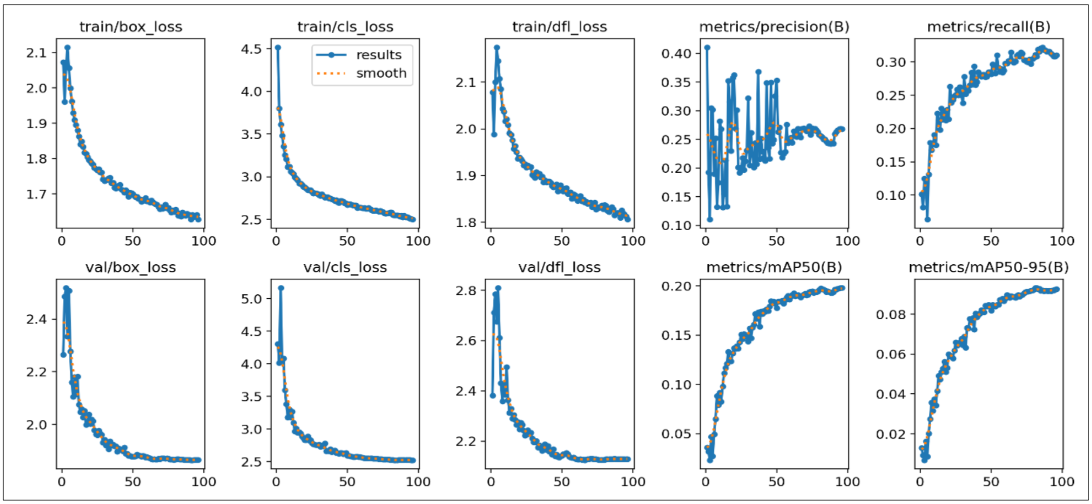
4.1 Model results

The overall performance of the model on the test set was evaluated using several key metrics, including Mean Average Precision (MAP), Precision, and Recall. The MAP (Mean Average Precision) observed 19.7%. This value provides an overall indication of the model's accuracy in predicting bounding boxes and correctly identifying the class of pavement distress. MAP of 19.7% suggests that while the model can detect objects and predict bounding boxes, there is room for improvement in achieving higher accuracy. The precision observed 25.4%, which measures the ratio of true positive predictions to the total positive predictions made by the model. In this case, a precision of 25.4% indicates that the model produces a moderate number of accurate predictions but also has false positives, meaning it sometimes predicts distress where there is none. Recall value was observed as 31.2%. Recall measures the proportion of actual positives that were correctly identified by the model. A recall of 31.2% suggests the model captures a reasonable portion of actual pavement distress cases, although some cases remain undetected.

Figure 3: Model Results



The Average Precision (AP) per class, as displayed in the horizontal bar graph, provides insight into how well the model performed on each distress type. Specific classes like "Alligator Cracking" and "Pothole" had relatively higher precision, while others like "Shoving" and "Ravelling" had lower precision. This variation might indicate an imbalance in the dataset or certain classes being more challenging to detect due to visual similarities with other classes.

4.2 Improvements in model

The model demonstrates a promising starting point, particularly in recall and class-specific accuracy for certain distress types. However, improvements in precision and MAP are

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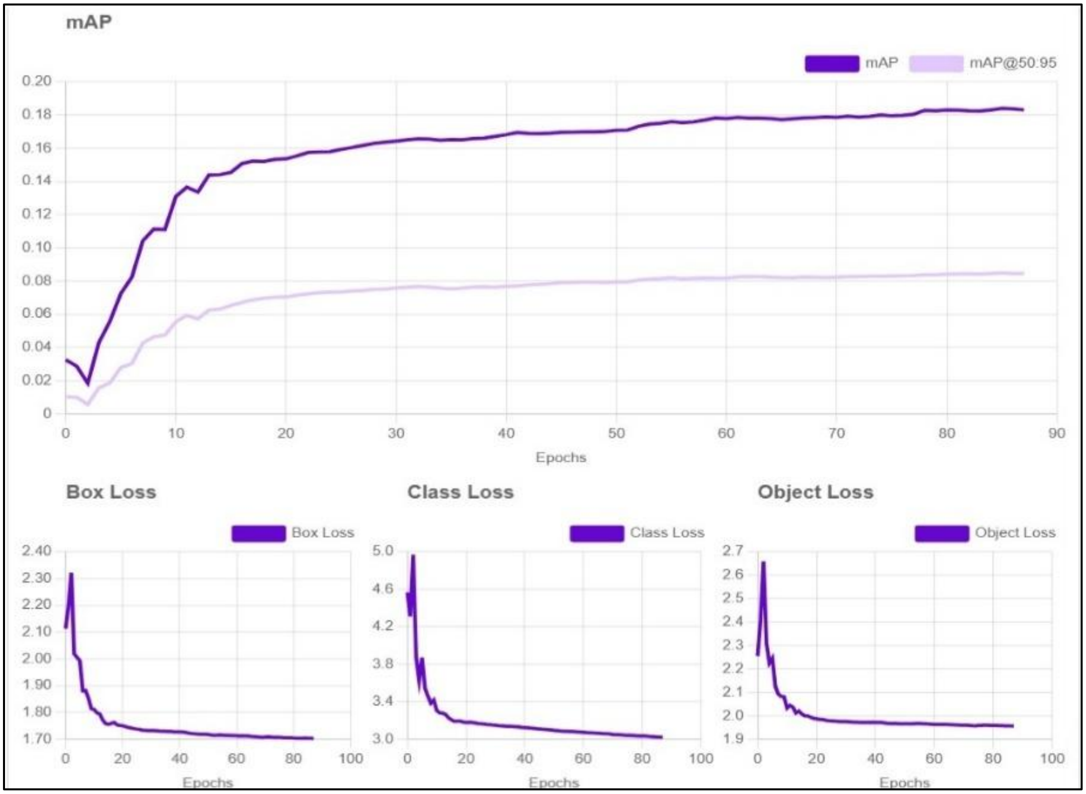
needed to make the model more reliable. Some recommendations for further enhancement include data augmentation, hyperparameter tuning, balancing classes and fine-tuning the model. Data augmentation helps to increase the dataset size or using techniques such as rotation, flipping, and contrast adjustment were done to help the model generalize better, especially on distress types with lower precision. Hyperparameter tuning and further experimentation with learning rates, batch sizes, and regularization methods could enhance model stability and performance. With more fine-tuning of the model, the precision is increased from 25.1% to 34.1%, which shows the better results for detection of raw pavement images.

Figure 4: Model Improvement Results



5.0 Conclusions

Pavement Asset Management System (PAMS) is a tool used for maintaining the deterioration of the pavement, by assessing the actual condition of the pavement which helps to allocate the budget for repairing the pavement. For assessing the pavement, the Pavement Condition Index (PCI) is one of the parameters for which functional evaluation of the pavement

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needs to be done, where the distress types and severity is measured. For automation of distress detection, many machine learning models are been used, but most of them are used for only crack detection, still, there are many other distress data needed for the calculation of PCI values as per IRC:82. Therefore, in this study, all other types of distress are also considered and the model is developed to classify the distresses.

Cracking, Alligator Cracking, Pothole, Sealing, Shoving, Patching, and Raveling are the seven types of distresses that are considered for model development, where a total of 14,953 images were obtained from different open-source databases. These images were annotated in the Roboflow platform and were trained first with the YOLOv5 model with no tuning, results obtained were MAP as 19.7%, Precision as 25.4%, and recall as 31.2%. For the further improvement of the model, hyperparameter tuning, data tuning and also while detection some thresholds were changed, by which Precision increased to 34.1%.

YOLOv5 model was trained using open-source database, which are mostly developed from developed countries, so in future these models should be trained using real collected images for Indian field conditions and based on that model further detection of distresses could be done for Indian conditions. Also, the YOLO trained model was able to detect only the surface distresses, which are visible, but there are other distresses like rutting which is due to deformation, depth of crack and potholes for knowing severity level of distress and also to calculate PCI value, so that pavement conditions can be evaluated. After this detection of distress types and their severity, one can also detect the amount required for repairing and maintaining the whole pavement.

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