Road Deterioration detection A Machine Learning-Based System for Automated Pavement Crack Identification and Analysis

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***Abstract*— Road surfaces may deteriorate over time because of a number of external factors such as heavy traffic, unfavourable weather, and poor design. These flaws, which may include potholes, fissures, and uneven surfaces, can pose significant safety threats to both vehicles and pedestrians. This research aims to develop and evaluate an automated system for detecting and analyzing cracks in pavements based on machine learning. The research explores the utilisation of object detection techniques to identify and categorize different types of pavement cracks. Additionally, the proposed work investigates several approaches to integrate the outcome system with existing pavement management systems to enhance road maintenance and sustainability. The research focuses on identifying reliable data sources, creating accurate and effective object detection algorithms for pavement crack detection, classifying various types of cracks, and assessing their severity and extent. The research objectives include gathering reliable datasets, developing a precise and effective object detection algorithm, classifying different types of pavement cracks, and determining the severity and extent of the cracks. The study collected pavement crack images from various sources, including publicly available databases and images captured using mobile devices. Multiple object detection models, such as YOLOv5, YOLOv8, and CenterNet were trained and tested using the collected dataset. The proposed approaches were evaluated using different performance metrics, The achieved results indicated that the YOLOv5 model outperformed CenterNet by a significant margin.**

Keywords*— *object-detection; YOLO; data; bounding-box; computer-vision

I. INTRODUCTION

The recognition of the significance of road infrastructure has only been recently emphasized with the expansion of global communication and transportation networks. Research conducted by [1] reveals that the construction of new road infrastructure provides local businesses with benefits such as increased productivity and job creation. Moreover, improving existing road systems can have substantial environmental advantages. According to reference [2] modifications to road infrastructure can lead to reduced regional CO2 emissions, particularly in areas with high traffic volumes. While road infrastructure offers advantages, it is essential to address concerns regarding accessibility and equitable distribution. Reference [3] emphasize the importance of addressing borders and multilateral opposition to mitigate the adverse effects of transport infrastructure improvements on disadvantaged groups. Over time, road surfaces can deteriorate owing to factors like heavy traffic, adverse weather conditions, and inadequate design. Such flaws, including potholes, cracks, and uneven surfaces, pose significant safety risks to vehicles and pedestrians. However, detecting these problems can be challenging, expensive and time-consuming, particularly with conventional inspection methods. The substantial extent of road infrastructure worldwide makes manual examination by trained individuals impractical and cost ineffective. Additionally, traditional methods like visual inspection and ground-penetrating radar may invariably miss detection of hidden or underground damage. Pavement cracks, a common issue in road infrastructure, pose a serious threat to the safety of vehicles and pedestrians.

The aim of this research is to develop a machine learning based system for automated pavement crack detection and analysis. In particular, the research will investigate how to identify and categories various pavement crack patterns using object detection techniques like YOLO (You Only Look Once). Through classifying different types of pavement cracks, including longitudinal, transverse, and alligator cracks. As well as assessing the severity and extent of pavement cracks, such as crack width, length, and depth

II. LITERATURE REVIEW

A. *Importance of Pavement Crack Detection and Classification First*

Road surfaces are seriously endangered by pavement cracks, which also jeopardize the structural integrity of the surfaces and put drivers at life threatening risk. These fissures have a negative influence on travel in a number of ways, including greater vehicle wear, decreased fuel economy, increased noise levels, and increased accident risks. To maintain safe and enduring road networks, it is essential to adopt accurate and efficient techniques for identifying and categorizing pavement cracks for swift fund allocation and management. The many forms of pavement cracks and how they affect traffic will be examined in this research. Longitudinal pavement cracks, which run along to the road's centerline and are influenced by elements like as ageing, traffic volume, and temperature changes, are the most typical form. According to [4], these fractures let water to seep into the pavement layers, causing severe harm and shortening the pavement's lifetime. Transverse cracks, on the other hand, appear parallel to the centerline and are brought on by changes in load and temperature. Transverse cracks weaken pavements, make them less skid-resistant, and make accident prone, according to [5]. Alligator cracks are a form of fatigue cracking brought on by repetitive loads and resemble the skin of an alligator. The structure of the pavement may be greatly impacted by these massive crevices, resulting in potholes and uneven surfaces. Different methods for precise and efficient pavement crack identification and categorization have been developed by researchers. Reference [6] utilize edge detection and morphological procedures in their beamlet transform-based method to identify pavement cracks with high accuracy and classify them into different groups. Reference [7] discusses machine learning, deep learning, and texture analysis-based methods for fracture identification and classification, concluding that deep learning-based methods excel in crack classification while machine learning-based methods are effective for crack detection.

B. *Computer vision and technologies*

Advances in deep learning and computer vision techniques have greatly contributed to the progress of object detection technologies. This literature review explores the development, applications, and challenges associated with object detection. Over the past two decades, object detection has significantly improved, moving beyond traditional computer vision methods like feature extraction and template matching. These methods had limitations in handling variations in object appearance, lighting conditions, and occlusions. However, the emergence of deep learning techniques, such as convolutional neural networks (CNNs), has revolutionized object detection by enhancing both accuracy and speed. Recent developments in object detection using deep learning, as reviewed by [8], are primarily based on two-stage detection frameworks like Faster R-CNN and Mask R-CNN.

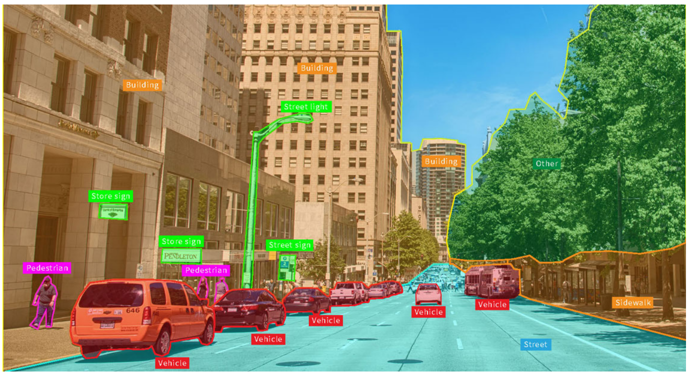


Figure 1: Object Recognition[24]

As illustrated in *figure 1* These frameworks utilize a region proposal network to generate potential object regions and then employ a detection network to classify and refine those regions. Single-stage detection frameworks like YOLO and SSD have also gained popularity due to their efficiency and simplicity. Another implemented technique is boosting chain learning, proposed by [9] which sequentially learns object detectors, selecting informative features for training subsequent classifiers in an iterative process that improves detection performance. Detecting foreground objects, especially in complex backgrounds, poses a significant challenge in object detection. Reference [10] introduced a statistical modelling approach capable of handling complex backgrounds for peripheral object detection. This method employs a mixture of Gaussians to represent the background and a probability map of the foreground for object detection. Performance metrics play a vital role in evaluating object detection algorithms. Reference [11] investigated various performance metrics, including mean average precision (mAP), intersection over union (IoU), and F1-score. The selection of appropriate metrics for the specific application and dataset is emphasized. A major hurdle in object detection is the availability of labeled training data. An approach for object identification utilizing transfer learning, which allows learning from a constrained number of samples, was suggested by [12].

C. *A Review of Recent Developments in computer vision*

Road fracture detection technologies based on computer vision have the potential to significantly advance transportation engineering. By facilitating the quick and precise diagnosis of fractures, these devices increase road safety, save maintenance costs, and lengthen the lifetime of road surfaces. Reference [13] creates an improved I-UNet convolutional neural network (CNN) for detecting different kinds of fractures in roads and shows how well it works. According to the research, the CNN has enhanced accuracy and efficiency when compared to other cutting-edge CNNs, making it a potential option for pavement maintenance. Reference [14] develop a user-friendly computer vision system that detects and categories problems on the surface of roads, demonstrating great accuracy in doing so. These systems perform even better because to research on data augmentation methods, loss functions, and image processing approaches. Engineers and planners may simply submit road images, assess detection findings, and make knowledgeable choices for pavement care thanks to the development of user-friendly interfaces.

D. *Object detection algorithms and uses*

Object detection is a prominent topic in computer vision with diverse applications in various fields. Deep learning has significantly advanced object detection methods. This literature review provides a comprehensive overview of different object detection algorithms, their advantages, and limitations. The sliding window approach involves moving a window across an image and applying an object classifier to detect objects. The region proposal-based algorithm addresses this issue by identifying candidate regions of interest using selective search. R-CNN, introduced by [15], incorporates object proposal, feature extraction, and object classification stages to improve detection accuracy. It overcomes the limitations of the region proposal-based algorithm but is computationally demanding. Fast R-CNN, Faster R-CNN, and Mask R-CNN are subsequent enhancements. Another popular algorithm is YOLO, which rapidly and accurately detects objects by dividing the input image into a grid and predicting bounding boxes, class probabilities, and confidence scores. Researchers have continuously improved the YOLO algorithm, including variations like Tiny-YOLO and YOLO-LITE. SSD is another fast and accurate object detection algorithm that predicts object categories and bounding boxes in a single pass. Modifications like feature map concatenation and feature fusion have been proposed to enhance its performance. These algorithms have been extensively studied, with [16] demonstrating successful detection of apple fruits using YOLOv3, and [17] proposing improvements to SSD.

E. Current studies to solve similar problem

Researchers have proposed various methods for pavement crack detection using object detection algorithms based on machine learning. A methodology that uses the YOLO v3 algorithm to find pavement cracks was described by [18]. To accomplish accurate identification of various kinds and configurations of cracks, the system uses data collecting, preprocessing, and the YOLO v3 algorithm. Reference [19] described a technique for identifying pavement cracks from small-field photos by fusing a convolutional neural network (CNN) with a long short-term memory (LSTM) network. Their technology overcame the difficulties presented by constrained field pictures and performed better in fracture identification than conventional techniques. By using the characteristics of transformer networks often employed in natural language processing applications, Reference [20] offered a transformer network-based approach for pavement crack identification. This technique showed excellent precision in identifying fractures of varied shapes and sizes. The accuracy and effectiveness of these most recent improvements in object identification-based pavement crack detection are encouraging. To improve their effectiveness and usefulness in real-world circumstances, more study is necessary.

III. METHODLOGY

The study's methodology, the data gathered, and the analysis performed are the main topics of the methodology chapter. The research's goal is to create an algorithm based on object identification and machine learning for pavement crack detection. The experimental research design that forms the foundation of the technique used in this study enables the modification and control of variables to demonstrate cause-and-effect correlations. The independent variables in this research are several machine learning algorithms, whereas the dependent variables are the accuracy, sensitivity, and specificity of pavement crack detection.

A. Research Philisophy

The guiding principles for doing research are referred to as the research philosophy. A positivist research philosophy, which emphasizes the application of scientific procedures to acquire objective information, is employed in this study. According to positivism, there is an objective reality that can be seen and measured, and research may provide valuable and trustworthy results. The positivist method is appropriate for this research since it seeks to find variables that affect fracture how well computer vision-based systems can detect road fractures. The research provides impartial and trustworthy results by using scientific methods and data analysis tools. The positivist method is consistent with the study's goals of determining the elements that affect how well computer vision-based systems identify road fractures. The research may provide a thorough grasp of these aspects by taking a scientific approach.

B. Research Design

The overall strategy utilized to direct the research process is known as the research design. This study included both quantitative and qualitative data collection and analytic approaches as part of a mixed-methods research design.
A mixed-methods approach makes it possible to gather both quantitative and qualitative data, allowing for a full understanding of the research problem. The quantitative data provides a broad overview of their current usage, while the qualitative data provides detailed insights into the factors that impact the effectiveness of computer vision-based systems for identifying road cracks.

C. Data Collection and Description

The dataset used in this paper consists of 201 images with each image containing at least five different classes of pavement cracks. This dataset, comprising of 18 unique classes, is derived from the DSPS23 website [23].

The classes are listed as follows: longitudinal_high, longitudinal_low, longitudinal_medium, Grass, patch_high, manhole_high, transverse_high, transverse_low, transverse_medium, diag_high,diag_low, diag_medium, alligator_high, alligator_low, alligator_medium,block_low,block_high

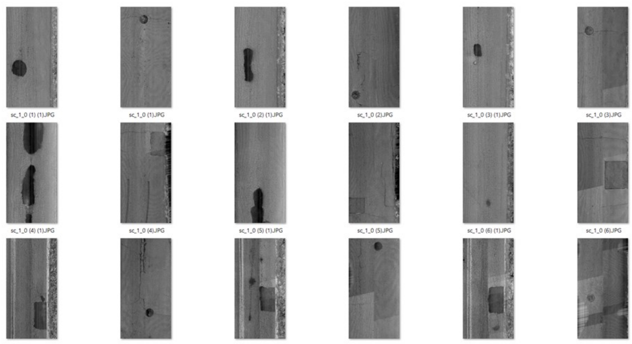


Figure 2: Image Dataset [21, 22]

The figure 2 shows the dimension and the quality of the image data which is used in this paper. Each image in the dataset is multi-labeled, creating a complex, multilabel classification problem. For example, a single image might feature a longitudinal crack, a transverse crack, and an alligator crack, simultaneously.

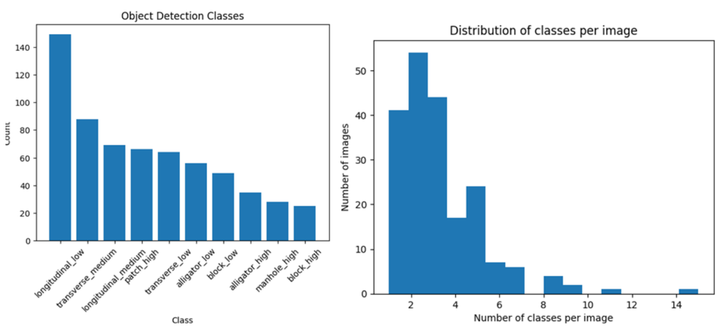
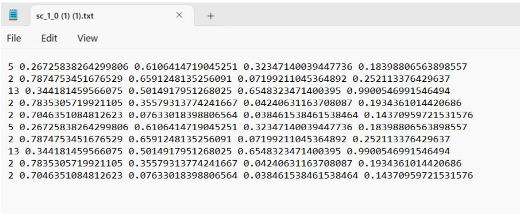


Figure 3: Distribution of Dataset

As shown in *figure 3* the distribution of each is quite unbalanced. The bounding box information for all the image files are given in the text file with the same name as of the images.

Figure 4: Annotation Files

The format in the text file is as follows:



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5 0.26725838264299806 0.6106414719045251 0.32347140039447736 0.18398806563898557
2 0.7874753451676529 0.6591248135256091 0.07199211045364892 0.252113376429637
13 0.344181459566075 0.5014917951268025 0.6548323471400395 0.9900546991546494
2 0.7835305719921105 0.35579313774241667 0.04240631163708087 0.1934361014420686
2 0.7046351084812623 0.07633018398806564 0.038461538461538464 0.14370959721531576
5 0.26725838264299806 0.6106414719045251 0.32347140039447736 0.18398806563898557
2 0.7874753451676529 0.6591248135256091 0.07199211045364892 0.252113376429637
13 0.344181459566075 0.5014917951268025 0.6548323471400395 0.9900546991546494
2 0.7835305719921105 0.35579313774241667 0.04240631163708087 0.1934361014420686
2 0.7046351084812623 0.07633018398806564 0.038461538461538464 0.14370959721531576
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Figure 5: Data Files of Border Information

As shown in *figure 4* and *figure 5* the annotation file provides bounding box annotations for object detection in images. Each row corresponds to an annotation for an object, with numbers indicating the class label, normalized coordinates of the top-left corner of the bounding box, and the width and height of the box, all ranging between 0 and 1. The image data of the pavement features seven main distress types, each annotated with bounding boxes. Participants are tasked with the systematic enhancement and modification of the dataset through various data cleaning, annotation, and augmentation strategies in order to improve the accuracy of a predefined model architecture.

D. Machine Learning Models Used

1) Yolov5 Model: You Only Look Once (YOLO) is a real-time object identification technique that has fundamentally altered computer vision. It has been improved iteratively since it was introduced in the year 2016. The YOLO architecture employs a single convolutional neural network (CNN) to forecast item bounding boxes and class probabilities from full pictures.

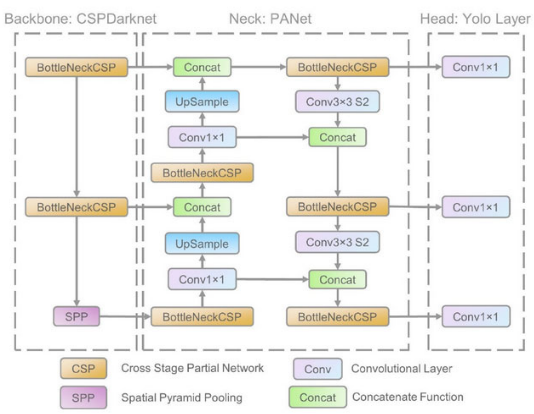

Figure 6: YOLOv5 Architecture [23]

As illustrated in figure 6 the design, allows YOLO to retain a high frame rate while providing state-of-the-art detection performance, makes it especially well suited for real-time applications.

2) Yolov8 Model: The latest YOLO version, YOLOv8, showcases recent advances in object detection, image categorization, and instance segmentation. Ultralytics, the firm behind YOLOv5, improved the developer experience with YOLOv8. YOLOv8's key change is switching from anchor-box offsets to direct prediction of object centres. This tweak speeds up Non-Maximum Suppression (NMS), which filters candidate detections post-inference, and makes box configuration forecasting simpler. YOLOv8 also alters convolutional structure.

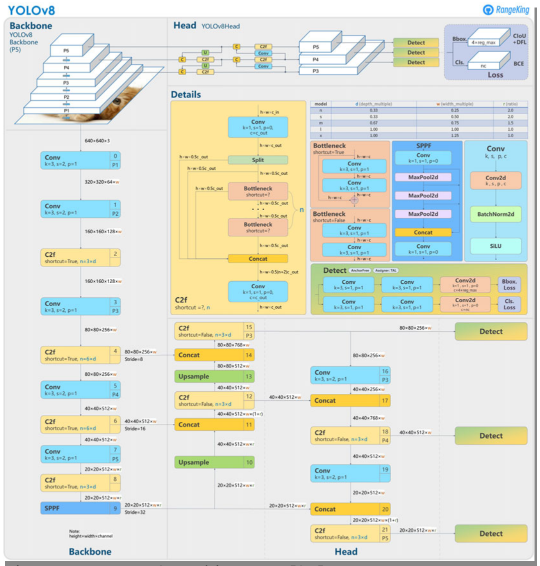

Figure 7: YOLOv8 Architecture. [25]

As shown in *figure 7* the fundamental building block is modified, and the stem's 6x6 conv becomes 3x3. C2f replaces C3 and combines all Bottleneck outputs from two 3x3 convs with leftover connections. C3 uses just the output from the final bottleneck. The Bottleneck's kernel size's initial conv is adjusted from 1x1 to 3x3. YOLOv8's direct neck feature concatenation eliminates the requirement for identical channel sizes. This reduces tensor size and parameters. Mosaic augmentation helps the model distinguish objects in new surroundings, respond to partial occlusion, and handle different pixels. YOLOv8's accuracy gains demonstrate these improvements' value. YOLOv8 has top-tier accuracy on the COCO (Common Objects in Context) test for object recognition models with similar inference latencies.

3) CenterNet Model: In order to locate item centres and ascertain an object's size and orientation, CenterNet, an object recognition method, relies on keypoint triplets. This approach increases accuracy while streamlining conventional object identification approaches' processing complexity.

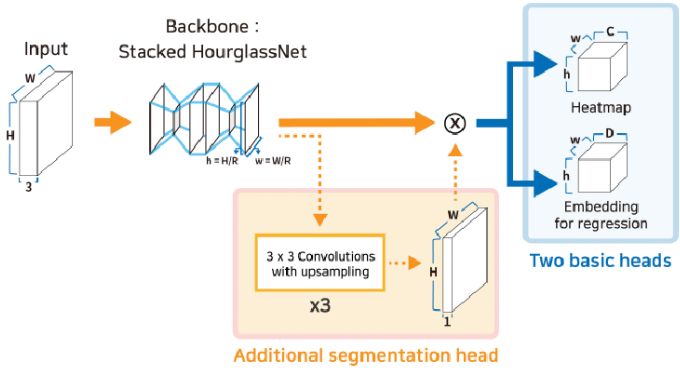

Figure 8: CenterNet Model Architecture [26]

As shown in *figure 8* CenterNet has been modified throughout time for a variety of applications, including 3D object identification for point clouds and real-time video object detection. It has also been used to identify things in certain domains, such fruit in photographs. The head, neck, and backbone make up the three primary parts of CenterNet's architecture. A deep convolutional neural network (CNN) serves as the framework and extracts certain characteristics from the input picture. A feature pyramid network (FPN) called the neck combines multi-scale features to improve feature representation. The head, which forecasts keypoints as well as object sizes and orientations, is made up of three parallel branches for classification, size regression, and orientation regression.

IV. Result and Analysis

A. *Evaluation of YOLOv5 model*

The analytical log reveals the model's performance on a testing dataset, which comprises 73 distinct class instances across 20 images. Performance metrics encompass precision (P), recall (R), mean average precision at an intersection over union (IoU) of 50% (mAP50), and mean average precision considering IoU values spanning between 50% and 95% (mAP50-95).

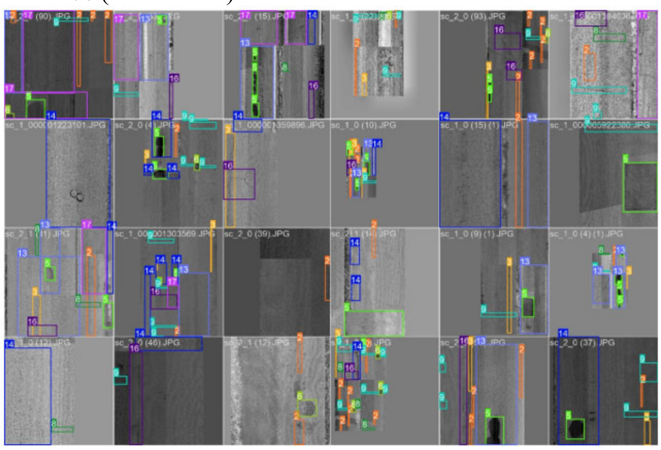

Figure 9: Crack Detection Result (YOLOv5)

The performance is illustrated in the *figure 9* The collective performance of the model for all classes reveals a precision of 0.465, indicating an accuracy rate of approximately 46.5% in object detection. The model's recall stands at 0.686, implying that roughly 68.6% of the total objects embedded in the images are identified. Furthermore, mAP50 and mAP50-95 are calculated as 0.645 and 0.348, respectively. The log provides additional insights into the performance metrics for individual classes within the testing dataset. Certain classes such as 'manhole_high' and 'alligator_low' exhibit superior performance concerning precision, recall, and mAP scores. Conversely, classes like 'longitudinal_medium' and 'grass' manifest comparatively substandard performance

B. *Evaluation of YOLOv8 model*

The YOLOv8 object detection model, endowed with 168 layers and a total of 3,009,158 parameters, exhibits moderate detection performance across a test dataset comprising 73 object instances and 20 images. As per the log, the performance metrics of the model feature precision (P), recall (R), mean average precision at an intersection over union (IoU) of 50% (mAP50), and mean average precision considering IoU values ranging from 50% to 95% (mAP50-95).

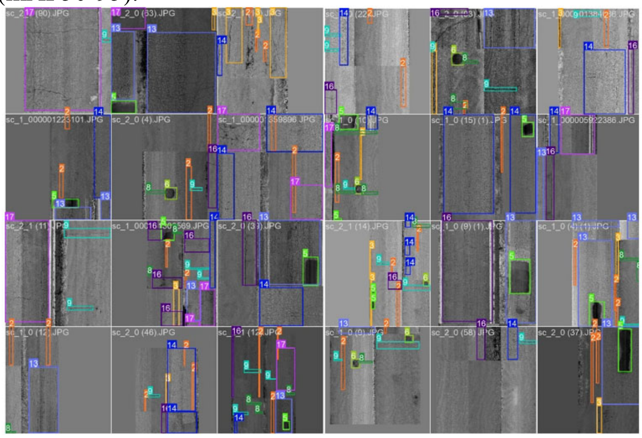

Figure 10: Crack Detection Result (YOLOv8)

As it can be seen in *figure 10* Cumulatively, the model boasts a precision of 0.52, implying a **52% success rate in object detection**, whereas a recall of 0.584, reflecting that nearly 58.4% of total objects present within the images are accurately identified. The mAP50 and mAP50-95 metrics are calculated as 0.6 and 0.355 respectively, further reflecting the model's performance. Class-specific performance metrics are also provided in the log, where classes such as 'manhole_high' and 'alligator_low' indicate high performance with respect to precision, recall, and mAP scores, while other classes, including 'longitudinal_medium' and 'transverse_medium', demonstrate relatively lower performance. Given this variable accuracy across distinct classes, improvement strategies could entail enriching the training dataset, introducing more diverse examples, fine-tuning the model architecture, or tweaking hyperparameters. Furthermore, it is crucial to consider the specific application and context for the model, as performance requirements may vary.

C. *Evaluation of CenterNet model*

The evaluation of the CenterNet model on a multi-class classification problem provides several key insights. Overall, the model exhibits an accuracy of just 0.25, indicating that only 25% of the model's predictions are correct. This low accuracy highlights the model's limited effectiveness in classifying the given data set. Moreover, when considering class-specific performance, significant disparities emerge. For instance, the classes "Alligator_low" and "Transverse_medium" show comparatively superior performance with precision values of 0.35 and 0.40, recall values of 0.48 and 0.55, and F1-scores of 0.46 and 0.55 respectively. Conversely, classes like "patch_high," "manhole_high," and "transverse_low" exhibit notably poor performance, with F1-scores of 0.00. Further issues arise from class imbalance. The unequal distribution of class representation - some classes having significantly more samples than others - might be negatively affecting the performance, with the model struggling to learn characteristics from underrepresented classes. The model's trade-off between precision and recall also differs across classes. Some classes present high recall but low precision, whereas others show the opposite, necessitating a balance depending on the application.

V. Conclusion

This paper has embarked on the task of developing an automated system for pavement crack detection and analysis using machine learning techniques. Three models, namely YOLOv5, YOLOv8, and CenterNet, were employed and their performances have been evaluated. In terms of precision, recall, and mean average precision scores, the YOLOv8 model yielded the highest performance, making it the most suitable for this specific paper. It is worth noting, however, that the performance of each model varied across different classes, highlighting the intricacies of object detection and the challenges posed by multilabel classification tasks.

There are many potential ways to improve the present system in the future. The models may be able to capture a wider variety of fracture kinds and circumstances with the gathering and annotation of a bigger, more varied dataset. Further, it is essential to address class imbalance that could potentially hamper model performance. Strategies such as data augmentation or oversampling of minority classes could be beneficial in this regard. In addition, hyperparameter tuning and architectural modifications of the models could be explored to optimize model performance further. Lastly, the integration of the proposed system with existing pavement management tools opens possibilities for comprehensive, automated pavement monitoring solutions. It is anticipated that the advances made in this paper will contribute significantly to the field of automated pavement analysis, with considerable potential for future exploration and development.

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