# USE OF MACHINE LEARNING FOR DEFECT DETECTION IN FLEXIBLE PAVEMENT

**BY**

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# PLAGIARISM

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# DEDICATION

I dedicate this project to God, who has been my guiding light and pillar of strength. I offer my sincerest gratitude to my parents. Mr. and Mrs. Enebeli, for their endless love, patience, and financial backing. To my siblings, thank you for your unwavering support and encouragement during challenging moments. May God's grace continues to be upon my family, now and forever, Amen.

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# ABSTRACT

Manual pavement inspection methods are slow, subjective, and often inconsistent, leading to delayed maintenance and increased road deterioration. This study was carried out to develop an automated, image-based system capable of detecting and classifying visible defects in flexible pavements using machine learning. The objectives of the study were to review existing pavement inspection techniques, collect and preprocess pavement image data, and design and train a model capable of identifying pavement failures accurately. The study was with the aim of improving the speed, objectivity, and reliability of pavement condition assessments.

A dataset of pavement images was obtained from the Edo State Ministry of Works, field surveys, and public sources. The images were annotated in YOLO format and augmented by flipping, rotation, cropping, and brightness adjustment. The YOLOv8 object detection model, implemented in Python using TensorFlow, PyTorch, and OpenCV, was trained on Google Colab with an NVIDIA T4 GPU. Training was performed at varying epochs (50, 100, and 200) and hyperparameters to optimize detection performance. The model's accuracy was evaluated using mean Average Precision (mAP) and recall metrics to assess its ability to detect cracks, potholes, and rutting in flexible pavements.

Results showed that the model achieved a mean Average Precision ($mAP_{50}$) of **0.68** and recall above **0.80** for visible defects such as potholes and alligator cracking, at a confidence level of **0.5**. The model was less effective in detecting faint, low-contrast linear cracks. This study concluded that YOLOv8-based models can effectively automate pavement distress detection, providing a faster and more reliable alternative to manual inspection. It is recommended that future work expand the dataset and explore enhanced training strategies to improve the detection of subtle linear cracks.

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# ACRONYMS

| | | |
|---|---|---|
| CNNs | - | Convolutional Neural Network |
| ML | - | Machine Learning |
| YOLOv8 | - | You Only Look Once version 8 |
| AI | - | Artificial Intelligence |
| 3D | - | 3 Dimensional |
| IP | - | Image Processing |
| Mask R-CNN | - | Mask Region- Based Convolutional Neural Network |
| YOLOv5 | - | You Only look Once version 5 |
| SVM | - | Support Vector Machine |
| UAVs | - | Unmanned Aerial Vehicles |
| PMS | - | Pavement Management Systems |
| MobieNetV3 | - | Mobile neural network version 3 |
| ResNet50 | - | Residual Neural Network 50 |
| VGG-16 | - | Visual Geometry Group 16 |
| GPR | - | Ground Penetrating Radar |
| GLCM | - | Gray Level Co-Occurrence |

# CHAPTER ONE

# INTRODUCTION

## 1.1 Background of Study

(Alaamri, et al., 2017), Pavement is a multilayered structural system designed to distribute vehicular loads across a broad area to prevent surface and structural failure. It is composed of three key layers: the subgrade, the subbase and the base layer, which includes a bituminous carpet and macadam. these layers work together to ensure the road can withstand both pressure from traffic and environmental conditions. Pavements are subjected to compression and tension forces and failure in any of the layers especially under stress can lead to visible surface cracking.

(Mohod & Kadam, 2016) defined flexible pavement as a layered pavement structure that transmits loads to the subgrade through gradual load dispersion across successive layers. It is primarily made up of bituminous materials and depends on the stiffness and interlocking of aggregates for strength. Flexible pavements are easier to construct and maintain, but they are more prone to deformation and require more frequent maintenance under heavy traffic or varying environmental conditions.

According to (Rollings & Rollings, 1991) pavement failure is a common and recurring problem. The result of such failures is not catastrophic like the collapse of a building or a failure of a dam, but they represent a serious financial loss and are a nuisance to the public. According to (Sharad & Gupta, 2013) pavement deterioration is described as the gradual process through which defects, also known as distresses develop in pavement surfaces. This happens under combined influence of traffic loading and environmental conditions. The deterioration process leads to the formation of issues such as cracks, ruts, potholes, and surface deformations, which compromise the safety, comfort and lifespan of the pavement.

The rapid development of road infrastructure is crucial for economic growth, transportation efficiency, and public safety. However, as road networks expand and age, pavement begins to deteriorate. Pavement failures such as cracks, potholes, rutting and surface wear pose hazards to road users and increases the cost of road maintenance.

(Ejiogu, et al., 2000) stated that rapid development, when not matched with adequate planning and infrastructure investment, can negatively affect economic growth and transportation efficiency. They argued that uncoordinated expansion leads to congestion, poor road conditions, and delays, which increase transportation costs and reduce productivity. These inefficiencies hinder trade, limit access to markets and services, and ultimately slow down broader economic development in the region.

Traditional method of inspecting pavements which includes manual surveys and visual assessment of pavements are time consuming, labor intensive and have higher chances of human error. Recent trend in machine learning have opened up new possibilities for inspecting pavements and detecting pavement failures.

(Ragnoli, et al., 2018) stated that traditional methods of pavement inspection are predominantly manual and rely on visual assessments carried out by trained personnel. These methods are often time-consuming, subjective, and prone to inconsistencies due to human error or varying expertise. While these techniques have been widely used, they lack the precision and repeatability required for consistent pavement condition monitoring and largescale infrastructure management.

Machine learning which involves training of the computer to perform specific functions. (Sholevar, et al., 2022) described machine learning as a family of powerful algorithms capable of automatically extracting features and decision rules from large and complex pavement 2 datasets.

They stated that deep learning models, particularly convolutional neural networks (CNNs), are highly effective in learning detailed patterns from pavement surface images, enabling them to detect, classify, and segment various pavement distresses with greater accuracy and speed than traditional image processing methods. Unlike conventional techniques that rely on manually crafted features, machine learning approaches adaptively learn from raw data, making them more suitable for managing the variability and complexity typical in real-world pavement evaluations. These models also generalize well to noisy or previously unseen datasets, an essential advantage for large-scale pavement network assessments. The authors noted that machine learning significantly improves the efficiency and automation of pavement condition monitoring but also pointed out limitations, including challenges in quantifying the severity and density of certain distress types, suggesting the need for continued research and model improvement.

This model will be trained on images collected from dataset (images) gotten from ministry of works Edo state and tested using pictures obtained from Ugbowo axis of Benin city, Edo state, Nigeria.

## 1.2 Statement of the Problem

In most parts of the world including Nigeria, Traditional method of inspecting pavement continues to rely heavily on manual visual surveyors or the use of specialized equipment by trained personnel. This method is labor intensive, inconsistent and relies solely on the judgement of the inspectors. It is equally not feasible over large roads and also in remote areas. As a result of these, pavement issues often go undetected until they become severe resulting to higher repair cost, reduced road quality and increased safety risk for motorist. This aligns with Rangoli et al. (2018), which highlight that manual inspection methods are subjective, inconsistent, and inefficient for large-scale pavement monitoring.

### 1.3 Aim of the Study

The aim of this study is to develop and evaluate a machine learning based approach for the accurate and automated detection of pavement failures, in order to improve road maintenance practices, reduce cost of inspection and enhance the longevity and safety of road infrastructure.

### 1.4 Objective of the study

The specific objectives of this study are to:

I. Review existing pavement inspection techniques and identify the limitations of traditional, manual methods.

II. Collect and preprocess pavement collection data, including images and sensor data, for training and testing machine learning models.

III. Design, implement, and train machine learning models capable of detecting and classifying pavement failures with high accuracy.

### 1.5 Scope of study

This study focuses on the design, development, and evaluation of a machine learning-based system for detecting surface defects in flexible pavements. The work covered several stages, beginning with the collection of pavement images from the Edo State Ministry of

Works and field surveys along the Ugbowo axis in Benin City. The images were processed and annotated using LabelImg and Roboflow to identify cracks, potholes, and rutting as the main defect types.

The model was designed and implemented using the YOLOv8 object detection architecture, developed with Python and supported by TensorFlow, PyTorch, OpenCV, and the Ultralytics framework. Google Colab served as the training and testing environment due to its GPU capability. Model performance was evaluated using mean Average Precision (mAP) and recall metrics on annotated test images.

The study also includes the conceptual design of a defect detection system that could be integrated into pavement management systems for automated maintenance planning. However, the scope is limited to visible surface defects on flexible pavements and does not cover subsurface or non-visible failures.

### 1.6 Justification of study

The condition of road pavements plays a vital role in transportation safety and economic development. In many developing regions, including Nigeria, pavement inspection is still largely carried out through manual visual assessments, which are time-consuming, subjective, and prone to human error. These limitations often delay the detection of pavement defects, allowing small issues to develop into major failures that increase maintenance costs, disrupt traffic flow, and cause avoidable road accidents.

This study is justified by the need to introduce automation and precision into pavement inspection through the use of machine learning. By leveraging computer vision techniques, specifically, the YOLOv8 algorithm implemented in the Python programming language, the system can automatically detect common pavement defects such as cracks, potholes, and rutting from images. This enables early detection, quicker decision-making, and efficient maintenance scheduling.

The adoption of this technology provides several advantages over traditional inspection methods. It allows for continuous and objective road monitoring, reduces the risk to inspectors working on active roadways, and minimizes cost and time in pavement evaluation. The outcome of this study will support government agencies, road maintenance departments, and construction firms in improving maintenance efficiency and ensuring safer road networks.

Beyond practical applications, the study also contributes to academic and technological advancement by demonstrating how artificial intelligence and civil engineering can be integrated to solve infrastructure problems. It expands the body of knowledge on the use of machine learning for smart city development and serves as a foundation for future research on intelligent transportation systems and automated infrastructure monitoring.

# CHAPTER TWO

## LITERATURE REVIEW

### 2.1 Introduction to Pavement Failures

Pavement failure is characterized by a decline in serviceability, primarily due to the development of cracks, rutting, and surface unevenness. Understanding the underlying causes of such failures is essential for designing effective maintenance and preservation strategies. Bituminous pavements often deteriorate due to a combination of structural, environmental, and material related factors. However, maintenance operations frequently rely on limited indicators such as cracking and rutting while neglecting other important forms of distress. Implementing corrective measures on the existing surface not only enhances the effectiveness of maintenance efforts but also extends the life of the pavement structures (Adlinge & Gupta, 2013).

Pavement failures can be categorized into two main types; structural and functional. Structural failures occur when the pavement cannot carry traffic loads without further damage, leading to visible distress such as rutting, potholes, and alligator crack. On the other hand, functional failures include issues like reduced skid resistance, surface irregularities, and water infiltration, which degrade the overall serviceability of the pavement without immediate structural implications. (Abdullah, et al., 2024.).

Pavement failure is typically defined as the reduction in serviceability due to manifestation of surface distresses such as cracks, potholes, and rutting. The deterioration process begins immediately after a road is opened to traffic, often progressing slowly at first and accelerating over time. Failures in bituminous pavements can result from wide range of factors or a combination of them, yet maintenance operations frequently focus on only a limited set of parameters namely unevenness index, cracking, and rutting while other forms of distress are often overlooked. To mitigate premature failures and reduce associated costs, it is essential to examine failed pavements to identify their root causes, and to adopt best practices in planning, design, construction and maintenance (Zumrawi, 2015).

## 2.2 Causes and Progression of Pavement Deterioration

(Alaamri, et al., 2017) said cracks and other pavement defects occur due to a combination of factors during and after construction. During construction, poor quality control, failure in subgrade or other layers, and improper asphalt laying techniques can initiate weaknesses. Post construction, common causes include temperature changes causing asphalt shrinkage, high stress from heavy or overloaded traffic, poor drainage, and environmental effects like rainfall. Specific cracks types like block cracking and longitudinal cracking are often tied to thermal stress while potholes and edge cracks may result from structural failures or inadequate lateral support.

A range of factors contribute to road pavement deterioration, including poor drainage, traffic overloading, expensive subgrade source, and the use of low-quality materials (Zumrawi, 2015).

Faults caused in construction due to weak construction quality are particularly significant (Tarawneh & Sarireh, 2013). Specific issues such as compromised air void system and infilling of marginal air voids can lead to premature deterioration (Rangaraju, 2002). The dynamic nature of road pavement further complicates maintenance of pavement in good condition. This underscores the need for improved construction practices, materials, and maintenance techniques to mitigate road pavement deterioration. A range of factors contribute to common road faults, including traffic overload, pavement age, road geometry, weather, drainage, construction quality, and materials.

Moisture infiltration is one of the primary causes of pavement distress. It weakens the pavement by reducing the strength and stiffness of the subgrade and base layers. Once water enters the pavement structure through cracks, it exacerbates rutting, potholes, and surface deformation. Heavy rainfall during rainy season causes significant moisture accumulation in pavement, leading to premature failures (Abdullah, et al., 2024.).

Cracks typically result from traffic loads and environmental factors, especially temperature fluctuations and moisture infiltration. Cracks create a pathway for water to enter the pavement layers, weakening the subgrade and speeding up the deterioration process. Rutting, the permanent pavement deformation along the wheel path, is another major cause of failure in the flexible pavement. It is primarily caused by the deformation of the subgrade or the lower layer of the pavement under repeated traffic loads. High traffic volumes and inadequate pavement design often exaggerate the severity of rutting (Abdullah, et al., 2024.).

Edge cracking develops at the edge of the pavement due to traffic loading, lack of proper support from the shoulder, poor drainage condition, or due to yielding of the underlying material. Fatigue cracking is caused by surfacing failure due to aging of binder and poor mix design or structural causes such as inadequate pavement thickness or failure of the pavement structural layers due to repeated traffic loading. Depression is obvious deformation in the pavement due to construction fault or differential movement of the pavement structure (Mekonnen, et al., 2024).

Pavement deterioration is caused by a lot of interrelated factors. A sudden increase in traffic loading, especially if a road was designed for lighter use, can lead to fatigue failures like alligator cracking. Temperature variation especially in extreme climates, contribute to issues like bleeding and cracking. Poor construction of shoulders leads to edge failures, while clayed subgrades can cause surface corrugations and unevenness. Poor drainage, especially during the rainy season allows water infiltration, weakening the pavement layers. Also, incorrect handling of bituminous materials such as overheating or cooling of bitumen affects its binding quality and compaction leading to structural defects and premature pavement failure. (Adlinge & Gupta, 2013).

### 2.3 Automated Pavement Inspection

The global road network has expanded significantly, but aging infrastructure is nearing critical maintenance limits. This increases the need for effective pavement preservation methods. Pavement distresses reduce driving comfort and road appearance. More importantly, they weaken structural strength, raising accident risks and harming long-term infrastructure sustainability. For instance, cracks wider than 5 mm often allow water damage during rains, speeding up base layer failure.

Regular and thorough pavement condition assessments are essential for maintaining road safety and infrastructure performance across all highway types. However, traditional manual inspections face major limitations in large-scale applications. For example, inspecting one kilometer of a four-lane highway manually takes 3-4 h, making it inefficient for extensive networks. This inefficiency has made automated detection technology necessary for improving maintenance efficiency. Modern pavement inspection systems now widely used vehicle-mounted LiDAR (Light Detection and Ranging) and UAV (Unmanned Aerial Vehicle) (Zhenglong Lv, et al., 2025).

With the rapid development of global infrastructure, road networks have become a vital cornerstone for economic growth and social development. However, pavement defects (such as cracks, rutting, and alligator cracks) severely compromise road safety, traffic flow, and service life, particularly in the context of rapid urbanization and surging traffic volumes, making this issue increasingly prominent. Traditional manual inspection methods are inefficient and prone to high omission rates, making them incapable of addressing the demands of vast road networks and increasingly complex inspection requirements. Therefore, developing efficient and accurate automated detection technologies has become an urgent task for enhancing highway maintenance efficiency, reducing maintenance costs, and ensuring road safety. (Jiangang Yang, et al., 2025).

Manual crack detection was a very common practice for localizing cracks on paved roads. However, the manual method lacks efficiency and accuracy, it is expensive because of the involvement of the domain experts. Moreover, it is considerable tedious, arduous, and time consuming because the experts monitor the cracks with the naked eyes by roaming along the roads. For lessening the workload of the experts and making the system fast as well as cost effective, researchers are bringing automation for crack detection. With the advancement of computer vision technology, various vision-based methodologies have already been developed for performing automatic crack detection.

AI-based technology demonstrates efficiency in terms of time and cost by swiftly assessing extensive areas. It presents greater consistency by mitigating human biases and, through appropriate training, holds promise in forecasting future road conditions. However, the initial setup cost involves investing in technology, as classification accuracy hinges on effective model training and substantial initial data collection. Moreover, the model's performance heavily relies on data quality and may overlook subtle details perceivable by a human inspector. Continuous updates and maintenance also form crucial requisites for sustained model accuracy and functionality (Deepak Satheesan, et al., 2024).

Digital image correlation is an optical system for measuring displacement and determining the surface deformation of the observed object, regardless of the type of material. Generally, it is a system composed of equipment for measuring and collecting data and a software package for their analysis and processing. (Ivana Baristic, et al., 2023).

There are two types of laser 3D scanners. Time-of-flight laser scanners and the second type is phase-shift laser scanners. Time of flight laser scanners produce a laser light pulse that is inverted on the target object. The sensor inside the instrument measures the time of flight of the optical pulse that is reflected on the surface. The main benefit of using a terrestrial laser scanning system is that it improves the measuring range and balance to achieve high accuracy and efficiency enhanced by measuring range and balance to achieve high accuracy and efficiency enhanced by measuring process time of flight with better speed, accurate scan technology, and implementing high speed imaging in all field work processes and data collection (Abdelhalim Azam, et al., 2023).

**2.4 Factors Influencing the Performance of Pavement**

(Adlinge & Gupta, 2013) stated that various factors influence the performance of pavement. First and foremost is traffic, especially heavy vehicle loads and their frequency, which can degrade the structure overtime. Moisture is another major factor that weakens the pavement layers, particularly the subgrade when water enters through cracks or rises via capillary action. The subgrade itself if too weak or inconsistent can cause failure. Construction quality such as poor compaction, material selection and layer thickness directly affect performance another is maintenance. Maintenance plays a vital role, timely and appropriate maintenance can extend pavement life, while delay leads to higher repair cost and more extensive damage.

### 2.5 Role of Machine Learning in Automated Inspection

The most crucial advantage of machine learning in pavement condition evaluation is their robust learning algorithms which lead to the ability to extract rules and features (i.e., pavement distresses) from pavement datasets. The machine learning models have had better performance in terms of accuracy and computational time than conventional Image Processing (IP) techniques because they effectively learn so many features and rules essential in detecting and evaluating pavement distresses due to their complicated patterns. This high performance is of significant importance in the case of pavement network evaluation which deals with massive datasets (hundreds of thousands of kilometers of roads) to monitor. Moreover, the ML models provide more generalization and result in better performance on unseen and noisy data than the traditional methods (Nima Sholevar, et al., 2022).

Despite the ML algorithms requiring specialized skills for writing codes, a considerable computational effort, and big data sets (especially during their training), these algorithms are able to manage, automatically and in a smarter and easier way with respect to the more traditional techniques, the big data set mentioned above (e.g., sensor data, sounds, images, etc.), allowing detecting patterns and trends with good accuracy and in a wide range of applications. (Flippo Pratico, et al., 2020).

(Saul Cano-Ortiz, et al., 2022) worked on improving pavement condition inspection by comparing manual methods with modern machine learning approaches. Manual inspection done through visual inspection is time consuming, labor-intensive, subjective and prone to human error. To address these challenges the study focused on machine learning with emphasis on computer vision and deep learning techniques, to automatically detect and classify pavement defects from road surface images. This model learns from annotated datasets and can identify various types and severities of pavement distresses such as cracks and potholes with greater consistency and efficiency. The machine learning complemented manual inspection with speed, accuracy and reliability making it a more effective tool for modern pavement condition assessment.

(Wada, 2016) worked on identifying the causes of deterioration in bituminous pavements and proposing solutions to reduce or prevent them, especially in developing countries where road failures are common and costly. In his study, he explained that pavement deterioration is primarily caused by factors such as heavy traffic loads, poor drainage, low-quality construction materials, climatic conditions, and substandard construction practices. He grouped pavement failures into four categories: surface deformation, cracking, disintegration, and surface defects each having its own set of causes. For instance, deformations like rutting and corrugation result from unstable layers or excess binder, while different types of cracks are caused by repeated vehicle loads, shrinkage, or poor subgrade support.

He also discussed how disintegration, such as potholes and patches, usually occurs after fatigue cracking or poor repair work, and surface defects like raveling, bleeding, and polishing arise from issues like material aging, excessive binder content, or weak bonding.

(Wada, 2016) emphasized that many of these failures can be mitigated with better pavement design, appropriate material selection, effective drainage, and timely maintenance. However, he also pointed out that in many developing countries, limited funding and poor road management make these solutions difficult to implement. He concluded by recommending improved standards, stronger construction methods, and regular maintenance as essential steps to extend pavement life and reduce long-term costs.

### 2.6 Flexible Pavement and It's Common Defect

(Rashid & Dr. Gupta, 2017) discussed that flexible pavement is one of the most widely used pavement types especially in developing countries like India, due to its ease of construction, cost effectiveness, and its ability to be repaired in stages. However, they emphasized that despite these advantages, flexible pavements are highly susceptible to distress and early deterioration when not properly constructed or maintained. According to the authors, the performance of a flexible pavement over time depends on several factors which includes the quality of construction material, layer thickness, subgrade support and traffic loading conditions. If these factors are poorly managed, the pavement will show signs of premature failure, affecting both serviceability and safety. Additionally, environmental conditions such as rainfall and temperature changes also play a significant role in weakening pavement structure over time.

In terms of defects, (Rashid & Gupta, 2017) provided clear classification and explanation of common types of pavement failures. Rutting one of the mentioned defects is the longitudinal surface depression that forms in the wheel paths and caused by repetitive traffic loads especially when the pavement material is not sufficiently strong or compacted. Alligator crack also known as fatigue cracking is a series of interconnected crack that looks like an alligator's skin. This defect indicates a structural failure of the pavement and usually occurs due to repeated traffic loads that exceeds the pavement capability. Potholes is another defect that was discussed. It is formed when water enters through the surface cracks, weakens the underlying layers, and leads to the breaking away of the surface materials. This is often found in areas with poor drainage or neglected performance. Edge cracking, which is developed along the edge of pavements due to lack of lateral support, traffic loading too close to the edge, or shrinkage in the asphalt mix. These defects lead to reduced service life of the pavement, increased maintenance costs, and potentially hazardous driving conditions if left unaddressed. Lastly, (Rashid & Gupta, 2017) emphasized on the importance of early detection and timely repair of such defects to ensure better pavement performance and user safety.

(Tamrakar, 2019) explains that flexible pavements are widely used in road construction to their layered structural design, which contributes loads effectively to the subgrade. These pavements typically consist of surface course made of bituminous material, supported by base and sub-base layers placed over the subgrade. He stated that the performance and longevity of flexible pavement depend significantly on proper engineering design, quality of materials, and thorough compaction during construction. These pavements are vulnerable to failure due to several external and internal factors, especially poor subgrade conditions, heavy traffic loading, water infiltration, and seasonal temperature variations. These factors lead to the weakening of pavement layers, causing distress and deterioration over time. He identified various defects that appear in flexible pavements, explaining their causes and implications. One major defect is alligator crack, which is a pattern of interconnected cracks resembling an alligator's skin. He attributed this to the fatigue of asphalt layers under repeated traffic loading, particularly when the underlying base or subgrade is weak. Another defect is longitudinal and transverse cracking, which he notes are often caused by shrinkage, temperature variations, and reflection of cracks from lower layers. Rutting was also stated as a deformation along wheel paths due to excess stress or weak support layers. He also explained that the development of potholes, which forms when water enters cracks, weakens the pavement, and causes chunks to be dislodged by traffic. Lastly, he spoke about raveling, a surface defect where aggregates come loose because of binder aging or improper mixing. These defects not only reduce the pavement's serviceability and ride quality but also increase maintenance demands and pose safety risk to road users.

(Zumrawi, 2015) identified flexible pavement defects including alligator cracking, longitudinal and transverse cracks, potholes, rutting, and bleeding. These failures were largely attributed to poor construction practices; excessive axle loads and environmental effects like high temperatures and water infiltration. His study emphasized on lack of proper maintenance and substandard materials worsened these conditions leading to reduced pavement life. He recommended strengthening design standards and improving maintenance practices to address these issues.

According to (Rashid & Gupta, 2017), flexible pavement defects are the result of structural and environmental stresses acting on the pavement over time, often intensified by substandard construction material and inadequate drainage systems. The authors explain that these defects include cracking, rutting, potholes, and surface deformations, each of which indicates specific failure mechanisms within the pavement layers. For instance, rutting results from the accumulation of permanent deformation in the subgrade or base course due to repetitive loading, while fatigue cracking results from the repeated flexing of the pavement under traffic loads, leading to structural breakdown. They emphasized that poor maintenance practices, heavy traffic and climatic factors like temperature fluctuations, moisture infiltration increases these failures. They also stress the importance of timely identification and rehabilitation of defects to prolong pavement lifespan and ensure road safety and the necessity for more systematic and scientific approaches in pavement evaluation and management.

According to (Khahro, 2022), defects in flexible pavements are a significant concern for sustainable infrastructure development, as they directly impact road performance, safety and maintenance costs. The author states various common types of pavement defects including cracking, rutting, potholes and surface wear which are caused by factors such as excessive traffic loading, environmental influences like temperature variation and water infiltration as well as poor construction quality and material deficiencies. He stated strongly that these defects not only reduce the functional lifespan of roadways but also lead to increased fuel consumption and greenhouse gas emissions due to poor driving conditions, thereby undermining sustainability goals. The study went further to state that early detection and timely maintenance are critical to mitigating the progression of these defects. He advocated the integration of advanced technologies such as pavement monitoring systems and data driven evaluation techniques to enhance defect identification and support proactive maintenance strategies. This approach would help achieve durable, cost effective, and environmentally sustainable road networks.

(Al-Arkawazi, 2017) in his work, stated that defects in flexible pavements are primarily the result of inadequate design, poor quality materials, environmental impacts and insufficient maintenance practices. The author explains that flexible pavements, which rely on layered systems to distribute loads, are vulnerable to various forms of deterioration when any layer fails to perform its intended function. Common defects that were identified includes alligator cracking, potholes, rutting and bleeding each were signified by different underlying causes such as structural fatigue, moisture penetration or asphalt binder excess. He noted that repeated traffic loading especially from heavy vehicles accelerates the progression of these failures, particularly when compounded by poor drainage and subgrade instability. The study centered on the importance of understanding these defects not only for repair purposes but also for enhancing pavement design and construction standards. The author advocates for improved material selection, regular inspection and timely maintenance in order to reduce the occurrence and severity of pavement defects, thereby extending the service life of road infrastructure.

Defects in flexible pavement are mainly caused by a combination of traffic loads, environmental conditions and material degradation over time. Types of pavement defects includes cracks, potholes and surface deformations which result from factors like poor drainage, subgrade instability and inadequate construction techniques. These defects compromise the structural integrity and serviceability of roadways, leading to increased maintenance cost and reduced user comfort. This study suggests the need for systematic monitoring and evaluation of pavement conditions to ensure timely intervention and to improve the longevity of flexible pavements (Nascimento, et al., 2021).

(Mosa, 2017) stated that flexible pavement defects arise due to several interrelated factors including traffic loads, environmental influences, poor material quality and construction flaws.

The author discusses that this defect commonly appears in form of cracks, ruts and surface distortions which not only compromise the functional capacity of the pavement but also pose safety risks to road users. He said that insufficient compaction, inadequate drainage and weak subgrade conditions are among the leading contributors to early pavement deterioration. The article points out that these failures are usually found in regions with extreme temperature fluctuations and heavy traffic particularly where maintenance practices are lacking. He advocates for better improved design methodologies, better quality control during construction and timely maintenance interventions as necessary strategies to mitigate pavement defects and ensure longer service life of road infrastructure.

(Lu & Hajj, 2021) in their study said defects in flexible pavements are primarily caused by structural fatigue, environmental conditions and material degradation overtime. They pointed out that repeated traffic loading leads to cracking and rutting, which are among the prevalent forms of pavement distress. They showed how moisture infiltration and temperature fluctuations can accelerate pavement deterioration, especially when drainage systems are inadequate. They stressed the importance of early detection and preventive maintenance enhance pavement life and reduce long term costs.

## 2.7 Traditional Method of Pavement Defect Detection

(Liang, et al., 2024) discussed the limitations of traditional pavement defect detection methods, they are time consuming, labor intensive and that they are subject to human error. The authors noted that conventional techniques typically involve manual inspection or the use of simple devices, which can lead to inconsistent results due to subjective judgements and varying inspector experience. They also stated that traditional approaches are not always efficient for large scale road networks, as they require manpower and resources, limiting their effectiveness in ensuring timely maintenance and long-term infrastructure sustainability.

The authors stated that traditional methods of pavement defect detection, particularly visual inspections, have been the standard of practice for many years but are increasingly seen as inadequate for modern infrastructure management. They explain that this method relies heavily on human judgement which can introduce subjectivity and inconsistencies in the evaluation process. They noted that manual inspections are time consuming and often lack the precision and efficiency required for large-scale or high traffic road networks. They argued that while traditional methods have played a significant role historically, there is a growing need for more automated techniques to enhance the accuracy and consistency of pavement conditions assessments (Thodesen, et al., 2012).

(Tello-Cifuentes, et al., 2024) explained that traditional methods of pavement defect detection, such as manual inspections and simple measurement tools, are limited in their ability to provide accurate, timely and consistent data. They pointed out that these approaches often suffer from subjectivity, as they depend heavily on the inspector's experience and perceptions leading to potential inconsistencies in defect identification and classification. These authors stated that traditional techniques are time consuming and inefficient, particularly for large scale infrastructure systems, making it difficult to implement preventive maintenance strategies effectively. Their work centered on the need for more advanced and automated solutions to improve the reliability and efficiency of pavement monitoring.

(Marecos, et al., 2017) stated that traditional methods of pavement defect detection such as visual inspections and basic surface evaluations are still used but come with several drawbacks. These methods are manual and time-consuming relying heavily on the inspector’s judgement which introduces subjectivity and the risk of inconsistent results. They noted that traditional techniques often fail to detect hidden or subsurface defects, limiting their effectiveness for comprehensive pavement assessment. They suggested that to improve the accuracy and efficiency of pavement monitoring, more advanced and automated methods are necessary.

(Tsai, et al., 2010) explained that traditional pavement defect detection methods which rely on manual visual surveys are limited by subjectivity, inconsistency and inefficiency. They observed that these techniques develop heavily on the experience and judgement of the inspectors which can lead to variability in defect identification. They also noted that traditional methods are time consuming and not well suited for large scale pavement networks as they require significant manpower and resources. Due to these limitations, the authors called for automated approaches that can deliver faster and more reliable pavement condition assessments.

## 2.8 Machine Learning in Flexible Pavements

(Marcelino, et al., 2021) discussed the application of machine learning in flexible pavement as a promising approach to improve the efficiency and the accuracy of pavement condition assessment and maintenance planning. They explained that machine learning models can process large volumes of data such as pavement images and performance indicators to automatically detect defects and predict deterioration trends. This allows timely decision making compared to traditional inspection methods. The authors concluded that incorporating machine learning into pavement management systems offers a practical pathway towards enhancing the sustainability and cost effectiveness of road maintenance operation.

(Inkoom, et al., 2019) examined the role of machine learning in improving the detection and evaluation of pavement defects, particularly in flexible pavement systems. They stated that machine learning algorithms especially supervised learning models, have the capability to analyze large and complex datasets to identify patterns related to pavement distress. The authors explained that these techniques can perform better than traditional methods by offering faster more consistent and data driven assessments, which are crucial for effective pavement maintenance planning. Their study supports the growing adoption of machine learning as a valuable tool in modern pavement management systems.

(Zeiada, et al., 2024) discussed the application of machine learning in flexible pavement as a means to enhance the accuracy and efficiency of pavement performance evaluation. They explained that machine learning models can process diverse datasets such as traffic loads, environmental conditions and material properties to predict pavement deterioration and detect early signs of failure. The authors described these techniques as effective in supporting proactive maintenance strategies and reducing lifecycle costs, offering a data driven alternative to conventional assessment methods.

(Kaloop, et al., 2023) presented the growing relevance of machine learning in the field of flexible pavement management, particularly for its ability to improve the prediction of pavement performance and automate the detection of surface defects. They explained that machine learning techniques can efficiently handle large datasets generated from pavement condition surveys, enabling more accurate forecasting of pavement deterioration. They described how the models support data driven decision making helping infrastructure managers prioritize maintenance activities and allocate resources effectively. Their work reinforces the importance of integrating intelligent systems into pavement management to enhance reliability and operational efficiency.

(Zhao & Wang, 2025) explored the use of machine learning as an effective approach for evaluating and managing flexible pavement conditions. Machine learning techniques were shown to enhance the ability to detect surface distresses such as cracks and rutting by analyzing large datasets from pavement monitoring systems. These models support improved prediction of pavement performance over time, enabling more informed and proactive maintenance planning. The study also shows that machine learning offers greater consistency and accuracy compared to traditional inspection methods, contributing to more sustainable and cost-efficient pavement practice.

### 2.9 Machine Learning Techniques Used in Pavement Defect Detection

(Sholevar, et al., 2022) explored the use of convolutional neural networks (CNNs) for automated pavement detection, showing that this machine learning techniques can accurately identify surface defects such as cracks from pavement images. CNNs were applied to large datasets, enabling reliable and consistent classification of defects without the need for manual inspection. This approach improves the speed and precision of pavement condition evaluation, and offering a more efficient alternative to traditional methods.

(Luo, et al., 2022) applied a learning technique known as Mask Region-Based Convolutional Neural Network (Mask R-CNN) for pavement defect detection. This method enables precise identification and segmentation of various surface defects, such as cracks and pothole, directly from pavement images. By using Mask R-CNN, the process achieves high accuracy in detecting the location and shape of defects while reducing the need for manual intervention. This approach enhances efficiency and objectivity of pavement condition monitoring and supports automated maintenance planning.

(Yusof, et al., 2024) discussed the application of various machine learning techniques in pavement defect detection, focusing particularly on the effectiveness of deep learning-based models. They stated techniques such as Convolutional Neural Networks (CNN), You Only Look Once version 5 (YOLOv5) and Region-Based Convolutional Neural Network (R-CNN) as commonly used approached for identifying surface defects like Cracks, potholes, and raveling from pavement images. These models are capable of learning visual patterns associated with different types of damage, allowing for high detection accuracy and reduced reliance on manual inspection. YOLOv5 was noted for its ability to detect multiple defects in real time with strong performance in speed and precision. By referencing these techniques, the work supports the advancement of intelligent systems in automated pavement monitoring.

(Ibrahim, et al., 2024) referred to various machine learning techniques applied in pavement defect detection, focusing on their effectiveness in automating inspection processes and improving accuracy. Techniques such as Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Random Forest were presented as valuable tools for identifying surface defects like cracks, potholes and rutting. SVM was described as suitable for smaller datasets, offering reliable classification performance. CNN, due to its ability to process and learn from image data, was used for precise detection of visual pavement anomalies. Random Forest known for handling large datasets with multiple input variables, was applied for robust classification tasks. These methods were introduced as efficient alternatives to manual inspections contributing to faster more consistent and data-driven pavement evaluation systems.

Machine learning techniques have been explored as effective tools for improving pavement defect detection, offering greater accuracy and efficiency compared to traditional inspection methods. In this context, Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and Decision Trees were applied to identify and classify defects such as cracks, potholes, and surface deformations. CNN was used for its strong performance in processing pavement images and detecting intricate surface patterns, while SVM provided reliable classification of defect types based on selected features. Decision Trees were utilized for their interpretability and ability to handle structured datasets. These techniques contributed to developing intelligent pavement monitoring systems capable of automating defect detection and supporting timely maintenance decision making. (Liang, et al., 2024).

### 2.10 Data Collection and Preprocessing for Pavement Defect Detection

Data collection and preprocessing were presented as fundamental stages in developing effective pavement defect detection systems. Image-based data acquired through drones, mobile cameras, and sensors mounted on vehicles served as the primary sources for collecting pavement condition information. The work described how such data must be carefully prepared before being used for machine learning, with preprocessing steps including the removal of noise, grayscale conversion, normalization and resizing of images to ensure uniformity. Techniques such as data augmentation like rotation, flipping, and brightness adjustment were applied to expand the dataset and improve model generalization. Annotation and labeling of defects such as cracks, potholes, and surface wear was also emphasized as essential for supervised learning. These procedures were necessary to ensure the accuracy and reliability of the defect detection models allowing them to operate effectively in diverse and real-world pavement condition (Shakhovska, et al., 2024).

(Nguyen, et al., 2016) stated that the accuracy and reliability of pavement defect detection depend significantly on well-structured data collection and preprocessing steps. Images were captured using vehicle-mounted cameras under consistent conditions to ensure clarity and uniformity. Preprocessing steps included grayscale conversion to simplify image complexity, normalization to standardized pixel intensity values and filtering techniques to remove background noise. Edge detection was used to highlight the contours of cracks and other surface anomalies while image resizing ensured compatibility with machine learning model input requirement. These processes were essential for extracting meaningful features and improving the performance of defect detection algorithms.

(Nguyen, et al., 2018) emphasized that effective pavement defect detection depends heavily on data collection and preprocessing. Data was gathered through high resolution images captured by vehicle mounted cameras, ensuring coverage of diverse pavement conditions. The authors detailed preprocessing techniques include image enhancement, noise filtration and normalization to improve image quality and consistency. They also stated the importance of image segmentation and feature extraction to isolate relevant defect characteristics from complex backgrounds. Data augmentation methods such as rotation and scaling were applied to increase dataset variability and improve the robustness of machine learning models. Accurate annotation of defects was noted as essential to support supervised learning and improve detection accuracy.

(Han, et al., 2022) in their study emphasized on the importance of effective data collection and preprocessing in the detection of pavement defects. They described the use of high resolution 3Dlaser scanning technology as a primary data collection method which provided detailed surface information essential for accurate defect identification. They noted that raw data acquired from the scanning process often contained noise and irrelevant background information which requires a thorough preprocessing stage. This included filtering to remove outliners, normalization to ensure consistency across different data samples and segmentation to isolate defect related features from the overall pavement surface. These steps were crucial for improving the reliability and performance of the subsequent defect detection models ensuring that only relevant and high-quality data were fed into the analysis pipeline. (Martinec and Boyarchikov, 2023) proposed an effective method for data collection and processing aimed at improving pavement defect detection. UAVs (Unmanned Aerial Vehicles) equipped with high resolution cameras were used to efficiently capture visual data across large pavement areas. The collected images were processed through steps such as image enhancing, resizing and noise reduction to improve clarity and consistency.

Data augmentation techniques like rotation, flipping and brightness adjustment were also applied to increase dataset diversity and enhance model generalization. These preprocessing methods were essential for preparing high quality input data for training deep learning models to accurately detect a range of pavement defects under varying environmental conditions.

## 2.11 Computer Vision and Deep Learning for Pavement Design

(Majidifard, et al., 2020) provided an in-depth review of the application of computer vision and deep learning in pavement design, showing how these technologies are revolutionizing traditional methods of pavement evaluation and infrastructure management. They explained that computer vision systems, especially when integrated with deep convolutional neural networks (CNNs), enable the automatic detection, classification, and quantification of pavement distresses such as cracks, potholes, and surface deformations with high precision.

These models are trained on extensive datasets of pavement images, allowing them to learn and recognize complex surface patterns and subtle defects that manual inspections may miss. The authors further noted that deep learning techniques not only support surface distress identification but also extract structural features and degradation patterns that are vital for predictive analysis and pavement performance evaluation. By linking visual data to mechanical and structural behavior, these technologies assist in making informed design and maintenance decisions. They concluded that the integration of computer vision and deep learning into pavement design enables faster, more consistent, and cost-effective inspection processes, paving the way for intelligent, data-driven infrastructure systems and smarter transportation networks.

(Sholevar, et al., 2022) explored the application of computer vision and deep learning in pavement design, focusing on how these technologies enhance automation and accuracy in pavement condition assessment. The study demonstrated that advanced image processing techniques, when combined with deep learning models such as convolutional neural networks (CNNs), can automatically detect and classify pavement surface defects, including cracks, potholes, and rutting. By using image data collected through mobile devices and unmanned aerial vehicles (UAVs), their approach supports large-scale, non-contact analysis suitable for various pavement environments. The authors developed a deep learning framework capable of extracting meaningful features from visual data, which can be used not only for defect detection but also for linking surface conditions to underlying structural performance. This connection supports better design decisions and long-term maintenance planning. The study concluded that integrating computer vision and deep learning into pavement design leads to more consistent, efficient, and data-driven infrastructure management.

(Lee, et al., 2024) explored the use of computer vision and deep learning methods for improving pavement analysis, with a particular focus on pavement marking inspection and night-time visibility assessment. A vision-based framework was developed using deep learning models to assess the condition and clarity of pavement markings under various lighting conditions, including nighttime scenarios. High-resolution images were collected using vehicle-mounted cameras, and deep neural networks were employed to detect, classify, and evaluate the visibility of pavement markings. The study demonstrated that deep learning models could reliably quantify the degradation of markings and identify quality issues that may compromise road safety. The computer vision system was also capable of estimating retro reflectivity an important indicator of night-time visibility without relying on expensive and labor-intensive traditional tools. It was concluded that integrating computer vision and deep learning into pavement analysis provides an efficient, scalable, and accurate method for monitoring pavement marking conditions, supporting safer and more effective roadway maintenance.

(Yusuf, 2024) conducted a detailed evaluation of computer vision and deep learning models for pavement analysis within Pavement Management Systems (PMS), focusing on their performance, architecture, and practical applications. The study compared four models MobileNetV3, ResNet50, VGG-16, and YOLOv8 using performance metrics such as accuracy, precision, recall, and F1-score. MobileNetV3, a lightweight CNN optimized for mobile and real-time applications, offered the fastest training and inference times but had a slightly lower F1-score due to its limited depth and capacity. ResNet50, known for its deep residual connections, achieved the highest accuracy and F1-score, making it ideal for detailed pavement assessments, though it required greater computational power. VGG-16 balanced accuracy and efficiency, delivering strong F1scores while being less resource-intensive, which made it suitable for routine pavement surveys. YOLOv8, a real-time object detection model, performed well in identifying multiple pavement defects on-site, combining high inference speed with a competitive F1-score that reflected strong precision and recall. The F1score, calculated as the harmonic mean of precision and recall, was particularly important in measuring the models' ability to maintain accuracy in both defect detection and classification. Yusuf concluded that integrating these models into PMS could significantly improve the speed, reliability, and frequency of pavement inspections, enable proactive maintenance and contribute to safer, longer-lasting road infrastructure.

The integration of computer vision and deep learning in pavement analysis is presented as a transformative advancement over traditional inspection methods, which are often manual, labor intensive, and prone to human error. Computer vision enables the automated processing of pavement images to detect and classify surface defects such as cracks, potholes, and surface deterioration. Deep learning, particularly through convolutional neural networks (CNNs), has proven effective in accurately recognizing and segmenting these defects from complex image backgrounds. Automated systems built on these technologies can analyze large volumes of data with minimal human input, thereby increasing the speed, objectivity, and consistency of pavement condition assessments. The use of high-resolution image datasets, along with data augmentation techniques, further enhances the training and performance of deep learning models. This technological approach is seen as a reliable and scalable method for supporting proactive maintenance planning, reducing inspection costs, and improving overall pavement management strategies. (Opara, et al., 2021).

### 2.12 Advantages of Using Machine Learning for Pavement Defect Detection

Machine learning provides notable advantages for pavement defect detection by automating the identification and classification of surface damages with high precision and speed. It enables noncontact, data-driven assessment, reducing reliance on manual inspections that are often time consuming and inconsistent. Machine learning models, especially deep learning architectures, can handle large-scale image data and extract relevant features for accurate defect recognition, even in complex conditions or varying lighting and surface textures. These models improve with continued training, increasing their adaptability across different road environments and defect types. This technological approach supports more proactive and efficient pavement management by enabling early fault detection and optimizing maintenance strategies (Bai, et al., 2024).

(Rasol, et al., 2022), Machine learning offers several key advantages for pavement defect detection, contributing to more accurate, efficient, and objective infrastructure monitoring. It enables the automatic identification of surface anomalies such as cracks, rutting, and potholes by learning from large datasets of pavement imagery and sensor data. Unlike traditional manual inspections, machine learning models can process high volumes of data quickly and consistently, minimizing human bias and error. The ability of these models to adapt and improve over time through retraining allows them to handle diverse pavement conditions and evolving defect patterns. By integrating machine learning with non-destructive testing techniques like ground penetrating radar (GPR), the detection of subsurface defects also becomes more precise. This synergy enhances the depth and reliability of pavement evaluation. The application of machine learning ultimately strengthens maintenance planning by enabling early detection, prioritization of interventions, and reduction of lifecycle costs.

According to (Guo, et al., 2023) machine learning offers several advantages for pavement defect detection. They emphasized that machine learning techniques significantly enhance the accuracy and efficiency of identifying various pavement defects compared to traditional visual inspection and manual methods. They pointed out that these models are capable of learning complex patterns from large datasets, enabling the automatic classification and detection of diverse types of surface distresses such as cracks and potholes with high precision. The study stressed on the scalability of machine learning models, which allows them to process vast amounts of pavement image data rapidly and consistently, reducing subjectivity and human error in assessments. Also, machine learning algorithms can continuously improve their performance over time through retraining with new data, making them adaptable to different pavement conditions and environments. The use of these intelligent models also contributes to cost-effectiveness by minimizing the need for frequent field surveys and allowing for real time monitoring through sensor and imaging systems. The article underlined that machine learning provides a powerful, data-driven approach to modernize pavement maintenance and decision-making processes.

(Bhatt, et al., 2021), Machine learning presents significant advantages for pavement defect detection by improving the speed, accuracy, and consistency of identifying surface and structural failures. It allows for the automation of defect classification tasks, reducing reliance on manual inspection methods that are often labor-intensive and subjective. Machine learning algorithms can be trained on large datasets comprising images and sensor readings to recognize patterns associated with different types of pavement distresses, such as cracks, potholes, and deformation. This capability enables efficient processing of complex data from varied sources, including unmanned aerial vehicles (UAVs) and ground-based sensors. The use of machine learning also supports scalable and real-time monitoring, making it suitable for large-scale infrastructure management. As a result, maintenance decisions can be better informed and more proactive, leading to extended pavement lifespan and optimized repair costs.

According to (Sholevar, et al., 2022) machine learning improves pavement defect detection by enhancing accuracy, efficiency, and objectivity compared to traditional inspection methods. It enables automated recognition and classification of pavement distresses by learning complex features from large datasets, reducing the need for manual inspections and minimizing human error. Machine learning models, particularly deep learning algorithms, effectively process visual data under diverse environmental and surface conditions, ensuring consistent identification of cracks, potholes, and other defects. These models are adaptable and capable of generalizing across various pavement types, making them suitable for widescale implementation. The study shows how combining machine learning with advanced imaging and data-driven techniques leads to more reliable detection, real-time monitoring, and better-informed maintenance planning, ultimately supporting cost-effective pavement management.

## 2.13 Challenges of Using Machine Learning for Pavement Defect Detection

(Sholevar, et al., 2022), Machine learning for pavement defect detection, while promising, also presents several challenges that impact its practical implementation. One major issue is the need for large, high-quality, and well-labeled datasets to train models effectively; collecting and annotating such data is time-consuming and resource-intensive. Variability in pavement materials, lighting conditions, camera angles, and environmental factors can also affect the performance and generalization of trained models. Another concern is the imbalance of data, where certain defect types are underrepresented, potentially leading to biased model predictions. Integrating machine learning systems into existing pavement management frameworks requires considerable technical expertise and infrastructure. The study also notes the challenge of interpreting deep learning models, as they often function as "black boxes," making it difficult for engineers to understand and trust their decisions without explainable outputs. These limitations must be addressed to fully leverage the potential of machine learning in real-world pavement monitoring.

(Tamagusko, et al., 2024) explained that machine learning faces several challenges in pavement defect detection, such as the limited availability of high-quality labeled data, variability in data acquisition conditions, and the lack of standardized datasets across regions. Inconsistencies in image resolution, lighting conditions, and pavement materials can reduce model performance and generalization. The complexity in interpreting deep learning models can also limit their acceptance in practical engineering applications.

(Chatterjee, et al., 2018) identified challenges in applying machine learning for infrastructure asset management, including pavement defect detection. They discussed issues such as data heterogeneity, difficulty in accessing reliable and consistent datasets, and the need for domain expertise to properly train and interpret machine learning models. They also emphasized that integrating machine learning into existing decision-making frameworks is complex due to technical, organizational, and interpretability barriers.

(Saberironaghi, et al., 2023) mentioned several challenges in using machine learning for pavement defect detection, including the difficulty of collecting large, annotated datasets necessary for training robust deep learning models. Variations in pavement types, environmental conditions, and lighting can affect model accuracy. Deep learning models also require significant computational resources, which can limit their practical deployment in real time or large-scale applications.

(Zhang, et al., 2018) pointed out challenges in applying machine learning to pavement defect detection, such as the sensitivity of deep-learning models to noise and inconsistencies in 3D pavement surface data. Differences in crack shapes, lighting conditions, and pavement textures can negatively influence detection accuracy. Limited availability of labeled data and the computational cost of training deep models also present significant barriers to effective implementation.

### 2.14 Review of Related Works

(Fan, et al., 2023) provide a comprehensive survey of deep learning and machine learning approaches for identifying defects in flexible pavements, highlighting the use of advanced models such as convolutional neural networks, transformers, and self-supervised learning for detecting various types of distress like cracks, potholes, and surface degradation. The paper meticulously examines challenges including dataset bias, lighting variations, and environmental interference, and discusses how contemporary strategies such as attention mechanisms, data augmentation, and hybrid architectures are employed to address these issues. By evaluating different techniques image classification, object detection, and segmentation the authors underscore the superior performance and generalization capabilities of machine learning based methods over traditional image-processing techniques. They also emphasize the importance of large, diverse datasets and robust model design for real-world application. Ultimately, this survey charts a clear roadmap for future research, advocating the integration of more scalable, interpretable, and field-deployable machine learning systems for proactive flexible pavement maintenance.

Machine learning techniques have increasingly been applied to detect and classify flexible pavement failures, offering significant improvements in accuracy and automation over traditional visual inspection methods. They explored the application of supervised learning algorithms to pavement distress detection, focusing on processing high-resolution images to identify defects such as cracks and potholes. Their work emphasized the importance of feature extraction and selection, using machine learning models capable of handling complex pavement textures and varying environmental conditions. They demonstrated that models trained on carefully curated datasets could achieve reliable detection performance, enabling more efficient and objective pavement condition assessments. Moreover, their research highlighted challenges including the need for large annotated datasets and robustness to lighting and surface variability. They concluded that machine learning holds considerable promise for transforming flexible pavement maintenance by enabling scalable, accurate, and cost-effective failure detection. (Radopoulou & Brilaskis, 2017).

(Alfwzan, et al., 2024) developed a machine learning-based method for identifying asphalt pavement patches by analyzing image features derived from statistical properties. Their approach utilizes the Gray-Level Co-Occurrence Matrix (GLCM) and other statistical measures to extract texture features from pavement images, which are then used to train machine learning models for patch detection. The study demonstrates the effectiveness of this method in accurately identifying pavement patches, which is crucial for maintenance and repair planning. The authors highlight the potential of integrating this approach into automated pavement inspection systems, offering a cost effective and efficient solution for pavement condition assessment. Their research contributes to the growing body of knowledge on applying machine learning techniques to civil engineering problems, particularly in the context of pavement maintenance.

(Roberts, et al., 2020) propose a cost-effective approach for monitoring flexible pavement conditions by employing deep learning techniques. Their study focuses on leveraging convolutional neural networks (CNNs) to analyze pavement images, enabling the detection and classification of various distresses such as cracks and potholes. The authors highlight the potential of using readily available smartphone cameras to capture high-resolution images, which are then processed using deep learning models to assess pavement health. This method offers a scalable solution for infrastructure management, particularly in regions with limited resources. The research underscores the importance of integrating advanced machine learning algorithms into pavement management systems to enhance decision-making processes and optimize maintenance strategies.

# CHAPTER THREE

## METHODOLOGY

### 3.1 The Study Area

The study area was Benin City because of the nature of flexible pavement distress caused by heavy traffic loads and drastic environmental conditions such as intense rainfall. Multi-source data collection was employed to ensure that the data collected was diverse and accurate. Data was obtained from publicly available datasets and images of pavement failures. Additional information was be sourced from Diarsa Global Integrated Services LTD. Visits to various streets within Benin City were undertaken to capture photographic images of flexible pavement failures. Further images were obtained from the Ministry of Works, Edo State.

### 3.2 Dataset Collection

High-resolution images of flexible pavement surfaces were collected from road networks within Edo State. Specifically, the images were obtained from the Ministry of Works, Edo State, which maintained a comprehensive collection of pavement condition photographs captured during routine inspections and maintenance activities. These images represented a wide variety of pavement failures, including cracks, potholes, rutting, and patching, captured under diverse environmental and lighting conditions. The dataset was supplemented with additional images collected during field visits to ensure comprehensive coverage of pavement distress types.

### 3.3 Data Annotation

The training and validation datasets were obtained from publicly available sources on Roboflow. These datasets had already been annotated in multiple formats such as Pascal VOC, COCO, and YOLO.

For this research, the YOLO format was selected and downloaded, as it was compatible with the model training requirements. The images were annotated to identify and label different pavement failure types, with each distress instance marked by a bounding box and assigned its corresponding class label according to the YOLO annotation standard. Annotation tools such as LabelImg and Roboflow were used to review and validate the dataset annotations where necessary. The model was trained to detect seven pavement distress classes: alligator cracking, edge cracking, longitudinal cracking, patching, pothole, rutting, and transverse cracking.

### 3.4 Data Preprocessing and Augmentation

Before training the model, the images were resized to 640×640 pixels, which was the size that YOLOv8 required. The colors and brightness of the images were adjusted to improve the model's performance under different conditions. Additional versions of each image were created by flipping, rotating, or changing the lighting. This helped the model learn better by being exposed to more diverse examples.

### 3.5 Model Architecture

The proposed pavement distress detection model was based on the You Only Look Once version 8 (YOLOv8) architecture developed by Ultralytics. YOLOv8 was a single-stage object detection network that performed real-time detection and classification of multiple objects within an image using a unified convolutional neural network.

The YOLOv8 model architecture consisted of three major components:

I. **Backbone:** used for feature extraction from input images.

II. **Neck:** responsible for feature aggregation and fusion at different scales.

III. **Head:** performed object classification and bounding box regression.

For this study, the YOLOv8n (nano) variant was used due to its lightweight design and suitability for limited GPU resources while maintaining competitive accuracy. The pretrained weights were fine-tuned using the pavement distress dataset.

### 3.5.2 Neck (Feature Fusion Layer)

The neck of YOLOv8 combined features from different stages of the backbone using a Path Aggregation Network (PANet) structure. This enabled the model to:

I. Fuse semantic features from deep layers with fine-grained spatial features from shallow layers.

II. Strengthen localization accuracy and object boundary detection.

The neck therefore ensured that the model performed effectively on objects of varying sizes, which was critical for detecting pavement distresses that differed in scale and shape.

### 3.5.3. Head (Detection Layer)

The YOLOv8 detection head predicted three key outputs for each detected object:

I. Bounding box coordinates (x, y, width, height)

II. Objectness score, which indicated the probability of an object being present

III. Class probabilities, which identified the specific pavement distress type

Unlike previous YOLO versions that used anchor boxes, YOLOv8 employed an anchor-free detection mechanism, which simplified the prediction process and improved adaptability to different data.

Table 3.1: Parameters and description for model training

| PARAMETER | DESCRIPTION |
|---|---|
| BASE MODEL | YOLOv8n (Nano) |
| **IMAGE SIZE** | 640 × 640 pixels |
| **BATCH SIZE** | 64 |
| **EPOCHS** | 50, 100, 200 |
| **LEARNING FRAMEWORK** | Ultralytics YOLO (PyTorch) |
| **OPTIMIZER** | SGD / Adam (default in YOLOv8) |
| **LOSS FUNCTIONS** | Bounding box regression loss, objectness loss, classification loss |
| **ACTIVATION FUNCTION** | SiLU (Sigmoid Linear Unit) |

### 3.5.4 Classes

The model was trained to detect seven pavement distress classes, namely:

I. Alligator cracking

II. Edge cracking

III. Longitudinal cracking

IV. Patching

V. Pothole

VI. Rutting

VII. Transverse cracking

Each annotated instance in the training dataset was enclosed by a bounding box and labeled according to these classes.

### 3.5.5 Output Layer and Inference

During inference, the trained model output a set of bounding boxes with confidence scores and class labels for each detected distress type. Post-processing steps such as Non-Maximum Suppression (NMS) were applied to eliminate overlapping boxes and retain the most confident predictions. The results were visualized by overlaying bounding boxes and labels on the input pavement images.

## 3.6 Model Training

The labeled images were divided into three sets: a training set (used to teach the model), a validation set (used to check the model during training), and a test set (used to evaluate how well the model performed). This split helped prevent the model from simply memorizing the data. The training of YOLOv8 began using a method called transfer learning. This meant the model started from a version that had already learned to recognize objects from a large dataset (called pre-trained weights, such as from the COCO dataset). Using this pre-learned knowledge helped the model learns faster and more accurately on pavement images.

During training, several hyperparameters such as learning rate (how fast the model updated), batch size (how many images were processed at once), and number of epochs (training cycles) were adjusted to achieve the best performance. These settings were tuned using the validation set to ensure the mode learned correctly without making too many errors.

A special loss function that included box location, object detection, and class prediction was used to guide the training and help the model improve over time.

### 3.7 Performance Evaluation

After training, the model was tested on new images it had not seen before. The results were measured using accuracy, precision, recall, and F1-score to evaluate how well it detected pavement problems. The time it took to process each image was also recorded to determine if the model could operate in real time.

### 3.8 Deployment

The final trained model was used to build a system that could automatically detect pavement failures in new images. This system was designed to work on computers or mobile devices and was able to process images quickly and accurately. It identified different types of pavement distresses and showed their locations in the images to support road maintenance decisions. The system could be used by agencies responsible for roads and infrastructure, such as road maintenance departments, construction companies, or local governments. This tool helped them detect pavement issues faster, plan repairs more effectively, and improve the overall condition of road networks.

# CHAPTER 4

## RESULTS AND DISCUSSION

### 4.1. DATA PRESENTATION AND DESCRIPTION

The dataset used for this study consisted of pavement surface images that were collected and prepared for the purpose of training and testing the developed machine learning model for detecting defects in flexible pavements. The images captured various forms of pavement distresses that commonly occurs as a result of traffic loading and environmental effects. The major defect types considered in this study included cracks, potholes, raveling, and bleeding, which are typical indicators of pavement deterioration.

A total of 8000 images were used in the experiment. Out of these, 6,766 images were used for training, 783 images for validation, and 391 images for testing the performance of the model and 60 images were used for inferencing. The dataset was categorized into four major defect classes as presented in

**Table 4.1: Defect type and description**

| DEFECT TYPE | DESCRIPTION |
|---|---|
| CRACK | Transverse Crack, Transverse Crack, Edge Crack, Alligator Crack. |
| POTHOLES | Circular or irregular depression due to material loss |
| RUTTING | Longitudinal depressions from repeated traffic loads. |
| PATCHING | Repaired pavement area with surface irregularities. |

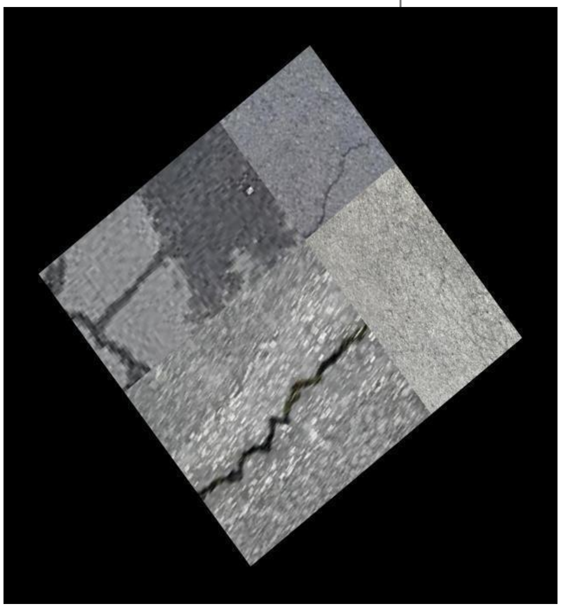


Fig 4.1: Transverse crack

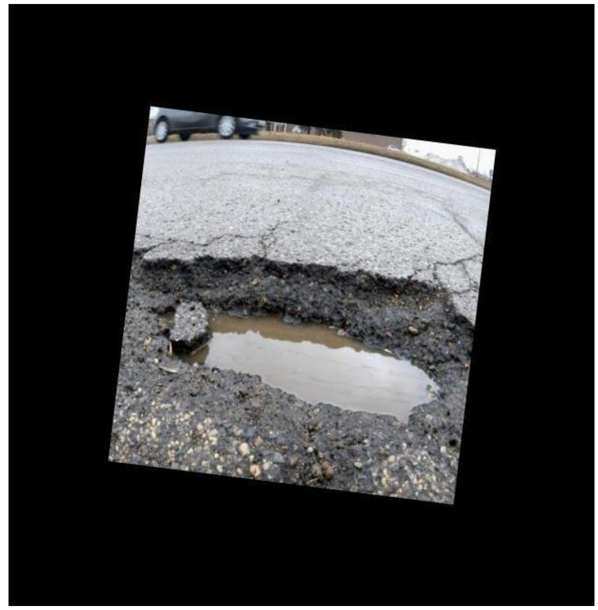


Fig 4.2: Potholes

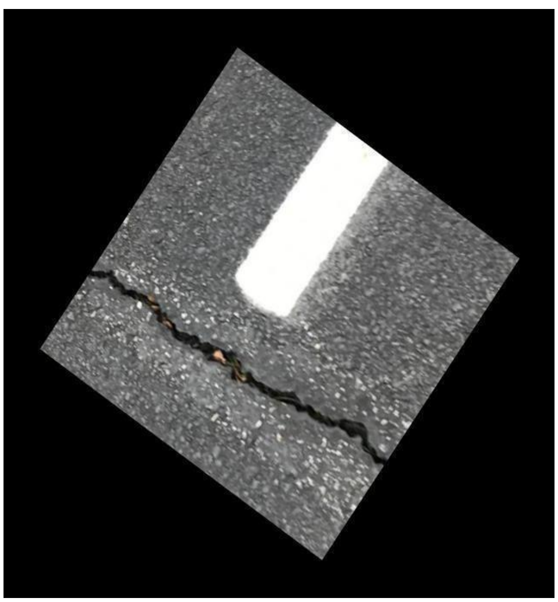


Fig 4.3: longitudinal crack

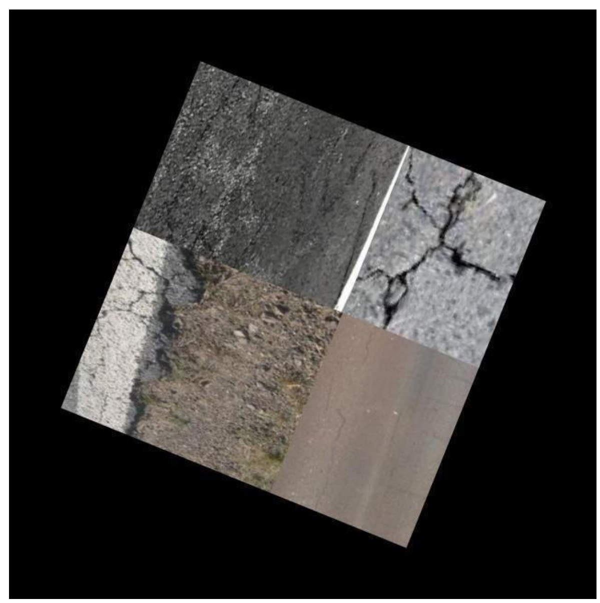
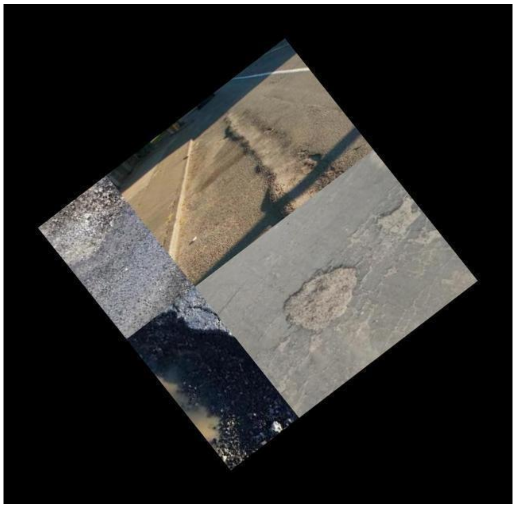


Fig 4.4: edge crack

All collected images were standardized by resizing them to 640 × 640 pixels to ensure uniformity in input dimensions for the YOLOv8 model. This preprocessing step was essential to maintain consistency across all samples, thereby facilitating efficient computation and improving the accuracy of feature extraction during model training. Each image was subsequently annotated using the Roboflow platform, where bounding boxes were manually drawn around visible pavement defects to indicate their precise locations within the image frame. The corresponding defect classes, such as cracks, potholes, rutting, and patching, were then assigned to each annotated region. This process of annotation enabled the creation of well-structured label files compatible with the YOLOv8 architecture, ensuring that the model could effectively learn to distinguish between different pavement distress types.

To enhance the robustness and generalization capability of the model, data augmentation techniques were applied to the dataset. These techniques included horizontal flipping, image rotation, and brightness adjustment, which artificially increased the variability of the dataset. Through these augmentations, the model was exposed to multiple orientations and lighting conditions, thereby reducing the risk of overfitting a condition where the model performs well on training data but poorly on unseen data. The inclusion of these transformations ensured that the trained model would perform reliably under diverse real-world conditions, such as variations in camera angles, lighting intensity, and pavement surface texture. The final dataset was compiled from a combination of field photographs captured from flexible pavement sections within Benin City, Nigeria, and publicly available pavement defect datasets accessed from sources such as Roboflow. The integration of both locally acquired images and external datasets provided a comprehensive and diverse data pool, encompassing a wide range of pavement distress patterns and environmental conditions. This diversity was critical to improving the model's learning capability and ensuring its applicability to broader pavement monitoring and maintenance systems.



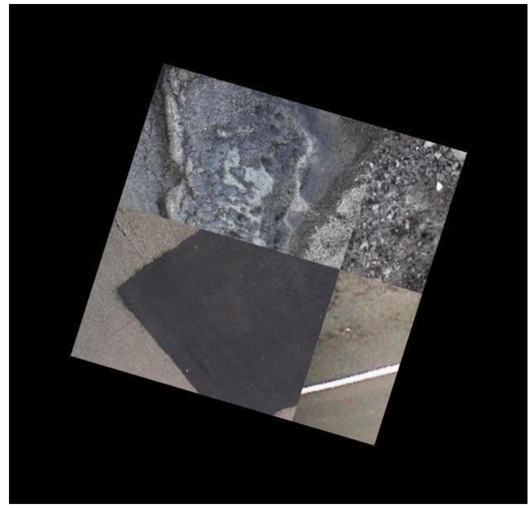


Fig 4.5: Patching pothole, rutting.

Fig 4.6: a section of road

**4.1.2 Experimental Setup**

```
# Install dependencies

!pip install torch ultralytics

!pip install opencv-python matplotlib numpy
```

The above command lines were used to install all necessary dependencies required for the implementation of the YOLOv8 model. The Torch library provided the deep learning framework for model training, while the Ultralytics package enabled access to the YOLOv8 architecture and its functions. OpenCV, Matplotlib, and NumPy were installed to support image processing, visualization, and numerical operations essential for data handling and model evaluation.

**Data Preparation** (Prerequisite):

```
# Ensure dataset is organized in required structure
# Annotations converted to YOLO format
```

I ensured that the dataset was properly organized according to the YOLOv8 model requirements. The images and their corresponding annotation files were arranged into *train*, *validation*, and *test* folders. I also converted all annotation files into the YOLO format, which specified the class label and normalized coordinates (center x, center y, width, and height) of each pavement defect. This process made it possible for the model to correctly interpret and learn the position and category of each defect during training.

**Training Execution**: #

*Run main training script*

python training.py

I executed the main training script by running the command python training.py. This script contained all the necessary configurations and instructions for training the YOLOv8 model on my prepared dataset. It initialized the model, loaded the training and validation data, set the learning rate, batch size, and number of epochs, and then began the training process. During execution, the model learned to identify and classify different pavement defects by adjusting its parameters through multiple iterations until optimal performance was achieved.

**Inference Demonstration** (Application):

# *Test on new images* python

inference.py

I tested the trained YOLOv8 model on new pavement images by running the command python inference.py. This step allowed me to evaluate how well the model could detect and classify pavement defects on unseen data, confirming its accuracy and generalization ability.

### 4.1.3 Code Execution and Implementation Workflow

#### 4.1.3.1 Training Pipeline Execution

```
import os
import cv2

import numpy as np
import matplotlib.pyplot as plt
from ultralytics import YOLO
import torch

print('CUDA available:',
torch.cuda.is_available())
print("GPU DEVICE:", torch.cuda.get_device_name(0) if
torch.cuda.is_available() else "No Device")

# --- Configuration ---

# Path to your dataset
DATASET_PATH = 'pavement_dataset'
TRAIN_IMG_DIR = os.path.join(DATASET_PATH, 'train', 'images')
TRAIN_LABEL_DIR = os.path.join(DATASET_PATH, 'train', 'labels')
VAL_IMG_DIR = os.path.join(DATASET_PATH, 'valid', 'images')
VAL_LABEL_DIR = os.path.join(DATASET_PATH, 'valid', 'labels')
TEST_IMG_DIR = os.path.join(DATASET_PATH, 'test', 'images')
TEST_LABEL_DIR = os.path.join(DATASET_PATH, 'test', 'labels')


# Define your classes (e.g., crack, pothole, patch)
# The order here must match the class_id in your annotation files
CLASS_NAMES = ['alligator cracking', 'edge cracking', 'longitudinal cracking',
'patching', 'pothole', 'rutting', 'transverse cracking']  NUM_CLASSES =
len(CLASS_NAMES)


# Model configuration
MODEL_TYPE = 'yolov8n.pt' # 'yolov8n.pt' (nano)
EPOCHS = 50 # Number of training epochs (adjust as needed)
BATCH_SIZE = 64 # Batch size for training (adjust based on GPU memory)
IMG_SIZE = 640 # Image size for training and inference
# Output directory for trained models and results
OUTPUT_DIR = 'runs/detect'  os.makedirs(OUTPUT_DIR,
exist_ok=True) # --- 1.
Create a YAML configuration file for YOLOv8 ---
```

```
# This file tells YOLOv8 where your data is and what your classes are.
data_yaml_content = f"""
path: {os.path.abspath(DATASET_PATH)}
train: train/images val: valid/images
nc: {NUM_CLASSES}

names: {CLASS_NAMES}
  data_yaml_path = os.path.join(DATASET_PATH,
'data.yaml') with open(data_yaml_path, 'w') as f:
f.write(data_yaml_content)   print(f"YOLOv8 data.yaml
created at: {data_yaml_path}")


# --- 2. Initialize and Train the YOLOv8 Model ---  print(f"\n-
-- Initializing YOLOv8 model: {MODEL_TYPE} ---") model =
YOLO(MODEL_TYPE) # Load a pre-trained YOLOv8n model    print(f"\n-
 -- Starting model training for {EPOCHS} epochs --
-")  results =
model.train(
data=data_yaml_path,
epochs=EPOCHS,
imgsz=IMG_SIZE,
     batch=BATCH_SIZE,    name='pavement_detection_model',   #
Name for the training run    cache=False # Cache images for
faster training
)

 print("\n--- Training complete! --
-")  print(f"Results saved to:
{model.trainer.save_dir}")


# --- 3. Evaluate the Trained Model (Optional but Recommended) --- print("\n--
Evaluating the trained model ---")
 # The best model is usually saved as 'weights/best.pt' in the run directory
 best_model_path = os.path.join(model.trainer.save_dir, 'weights',
 'best.pt') if
 os.path.exists(best_model_path):
    print(f"Loading best model from: {best_model_path}")

     trained_model = YOLO(best_model_path)
    metrics = trained_model.val(data=data_yaml_path,
imgsz=IMG_SIZE)
     print("\nValidation Metrics:")     print(metrics) # You can
access metrics like metrics.box.map else:

    print(f"Best model not found at {best_model_path}. Evaluation
skipped.")
```

```
 if not os.path.exists(best_model_path):

   print("Cannot perform inference as best model was not found after
 training.")
else:     for img_file in
 os.listdir(TEST_IMG_DIR):
         img_path = os.path.join(TEST_IMG_DIR, img_file)

        if not os.path.exists(img_path):
             print(f"Warning: Image not found at {img_path}. Skipping.")
            continue
          print(f"\nPredicting on:
 {img_path}")

        # Run inference with the trained model
inference_results = trained_model(img_path, imgsz=IMG_SIZE,
conf=0.50, iou=0.45)

         # Process results

         for r in inference_results:
             img = r.orig_img
            boxes = r.boxes.xyxy.cpu().numpy() # Bounding box coordinates
 (x1, y1, x2, y2)              scores = r.boxes.conf.cpu().numpy()
# Confidence scores               class_ids =
 r.boxes.cls.cpu().numpy().astype(int) # Class IDs
            # Draw bounding boxes and labels
for i in range(len(boxes)):                    x1,
y1, x2, y2 = map(int, boxes[i])
                  score = scores[i]
 class_id = class_ids[i]
                 class_name = CLASS_NAMES[class_id]
                   color = (0, 255, 0) # Green for bounding
boxes
                  label = f"{class_name}: {score:.2f}"
                   cv2.rectangle(img, (x1, y1), (x2, y2), color,
2)                   cv2.putText(img, label, (x1, y1 -
 10),
cv2.FONT_HERSHEY_SIMPLEX, 0.5, color, 2)



              # Display the result            plt.figure(figsize=(10,
8))
```

```
            plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
plt.title(f"Detection on: {os.path.basename(img_path)}")
            plt.axis('off')
plt.show()

print("\n--- Script finished ---")
```

In this stage of the research, I implemented the full experimental pipeline required for training and testing the YOLOv8 model for pavement defect detection. The process began by importing all the necessary Python libraries such as OpenCV, NumPy, Matplotlib, Torch, and Ultralytics. These libraries provided critical functions for image processing, numerical computation, visualization, and deep learning model operations. The setup also included a check to confirm that the NVIDIA T4 GPU was available and properly configured for computation. The GPU support was essential for speeding up the training process and efficiently handling large image datasets.

After the environment was configured, I defined the dataset directory structure, which included folders for the training, validation, and testing images and their corresponding label files. The labels represented the locations and categories of pavement defects such as alligator cracking, edge cracking, longitudinal cracking, transverse cracking, patching, potholes, and rutting. Clearly defining the dataset paths ensured that the YOLOv8 model could easily locate the data required for training and evaluation.

Next, I created a data configuration file (named data. yaml), which served as a bridge between the dataset and the YOLOv8 model. This file contained essential information such as the absolute path to the dataset, the location of the training and validation image folders, the total number of classes (nc), and the specific names of the defect classes. This configuration allowed the model to interpret the dataset correctly during training.

Once the dataset and configuration were ready, I initialized the YOLOv8n model (the nano version), which is an optimized and lightweight variant of the YOLOv8 architecture. This model was chosen because it offers a balance between speed**,** efficiency**,** and accuracy, making it suitable for practical applications like pavement defect detection. I then specified the training hyperparameters, including:

I. **Epochs (50):** representing the number of complete passes through the entire dataset during training.

II. **Batch Size (64):** the number of images processed before the model's parameters were updated.

III. **Image Size (640×640 pixels):** ensuring uniform input dimensions for all images during both training and inference.

The training process was then initiated by executing the training command, which enabled the model to learn distinctive features of different pavement defects. During training, the model adjusted its internal parameters (weights and biases) iteratively to minimize the detection and classification errors.

After completing the training phase, the best-performing model was automatically saved as **"best.pt"** in the weight's directory. I then evaluated the trained model using the validation dataset to assess its performance based on metrics such as precision, recall, and mean average precision (mAP). This evaluation helped determine how accurately the model could detect pavement defects and how well it generalized to unseen data.

Finally, I conducted inference testing on new pavement images from the test dataset. This step involved feeding unseen images into the trained model to visualize its prediction capability in real-world scenarios. The model successfully identified and localized defects by drawing bounding boxes and assigning labels (such as crack, pothole, or patching) with their corresponding confidence scores on each image. These visual outputs confirmed that the model was able to automatically detect and classify multiple types of flexible pavement distresses accurately.

### 4.1.4 Model Training and Validation Results

The training was carried out using the YOLOv8s model on Google Colab, utilizing an NVIDIA T4 GPU (16GB) to ensure faster computation. Transfer learning was applied by initializing the model with pre-trained weights from the COCO dataset, allowing the model to leverage previously learned visual features and adapt them to detect pavement defects more efficiently.

| Parameter | Value | Rationale |
|---|---|---|
| Model Variant | YOLOv8s (Small) | Selected for optimal balance between detection accuracy, training speed, and resource efficiency on Google Colab's NVIDIA T4 GPU. |
| Epochs per Run | 50 (Phase 1), 100 (Phase 2), 200 (Phase 3 & 4) | Conducted in phases to observe performance trends and prevent overfitting while improving model convergence. |
| Learning Rate | 0.001 (initial), reduced by 10% in later phases | A moderate learning rate ensures stable and gradual learning; reduction helps fine-tune weights for improved accuracy. |
| Batch Size | 64 | Balanced setting that optimizes GPU memory usage and stabilizes gradient updates during training. |
| Image Size | 640 × 640 pixels | Ensures uniform image dimensions, preserving feature details necessary for detecting small pavement defects. |

Fig 4.7: Parameters, Values and rationale

**Preprocessing**

1. Auto-Orient: Applied
2. Resize: Fill (with center crop) in 640 X 640 Augmentations

I. Flip: Horizontal vertical

**II.** Resize: Fill (with center crop) in 640 X 640

**III.** Crop: 0% Minimum Zoom, 17% Maximum Zoom

**IV.** Rotation: Between $-40^{\circ}$ *and* $+40^{\circ}$

These preprocessing steps were applied to standardize and enhance the dataset before training. The auto-orientation ensured that all images were properly aligned, while the resize operation adjusted each image to a fixed dimension of 640 × 640 pixels, matching the YOLOv8 input requirement. The applied data augmentations such as horizontal and vertical flipping, zoom cropping, and random rotations between −40° and +40° helped increase the variability of the dataset. This process improved the model's ability to recognize pavement defects under different lighting conditions, orientations, and viewing angles, thereby enhancing its overall accuracy and generalization performance.

Three key hyperparameters learning rate, batch size, and number of epochs were varied systematically across different training cases. The cases are summarized in Table 4.1

**Table 4.2: Learning rate, Batch size and Epochs**

| Case | Learning rate | Batch Size | Epochs | Remarks |
|---|---|---|---|---|
| Case 1 | 0.01 | 64 | 50 | Baseline configuration |
| Case 2 | 0.01 | 64 | 100 | Increased epochs with 50 |

| | | | | |
|---|---|---|---|---|
| Case 3 | 0.001 | 64 | 100 | Increased epochs to 100 and decreased learning rate by 10% |
| Case | 0.001 | 64 | 100 -200 | Increased epochs to 100 and decreased learning rate by 10% |

## 4.2 Model Training and Performance Analysis

### 4.2.1 Case 1: Learning Rate 0.01, Batch Size 64, Epochs 50

In the initial stage of training, I started the model with a moderate learning rate and a small batch size to allow it to learn steadily and avoid large errors. This means the model was gradually adjusting its internal parameters to correctly identify different pavement defects such as cracks and potholes. Over time, as the training continued for 50 complete cycles (epochs), the model's performance improved the total loss (which measures how far the model's predictions are from the correct answers) consistently reduced. This showed that the model was learning effectively and becoming more accurate in detecting pavement defects.

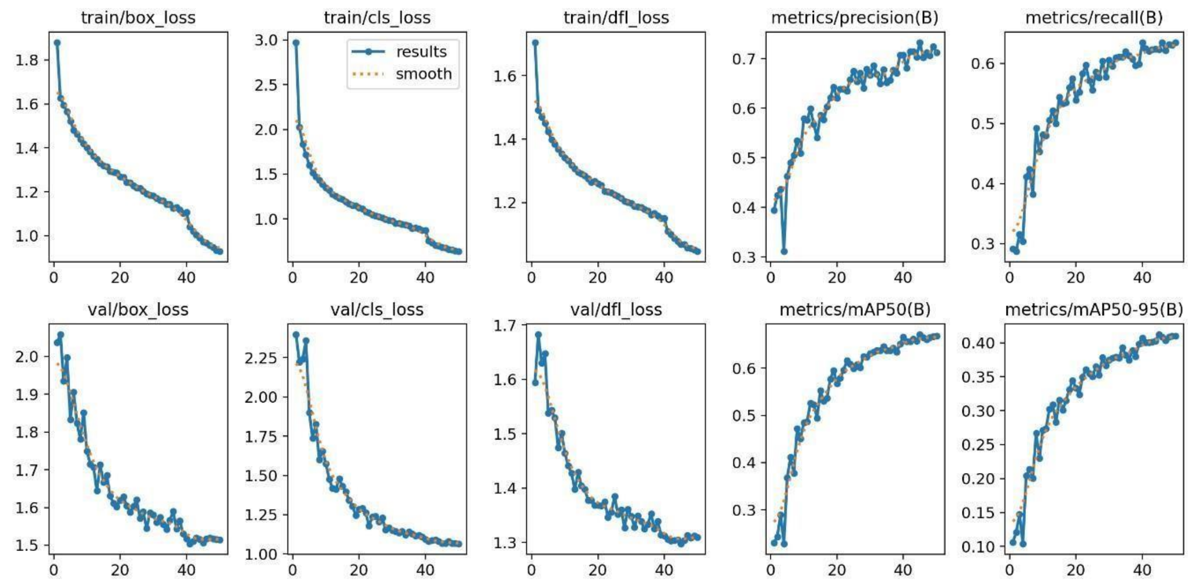



**Fig 4.8:** Training loss and mAP curves for Case 1.

Figure 4.7 shows the loss evolution for both training and validation processes.

1. During the training process, the box loss, classification loss, and DFL (Distribution Focal Loss) consistently reduced with each training cycle (epoch). This means the model was steadily improving in three key areas drawing more accurate boxes around pavement defects, correctly identifying the type of defect (such as cracks or potholes), and improving its confidence in each prediction. The continuous decrease in these losses showed that the model was learning effectively without overfitting (memorizing the training data) or showing instability (fluctuating performance). The model was becoming smarter and more reliable at detecting pavement defects as training progressed.
2. The validation losses closely followed the training losses, which indicated that the model performed consistently on both the training data and new, unseen data. This showed that the model was not just memorizing the training images but had actually

learned to detect and classify pavement defects accurately in different conditions, demonstrating good generalization performance.

3. Throughout the training process, the precision and recall values continued to rise, showing that the model was getting better at correctly detecting pavement defects and minimizing missed detections. The mAP50 (mean Average Precision at 50% Intersection over Union), which measures the overall accuracy of object detection, also improved significantly reaching about 0.68 by the 50th training cycle (epoch). This steady improvement showed that the selected learning rate and batch size allowed the YOLOv8 model to train smoothly and efficiently, resulting in stable performance and reliable detection of various pavement defects such as cracks, potholes, and patches.

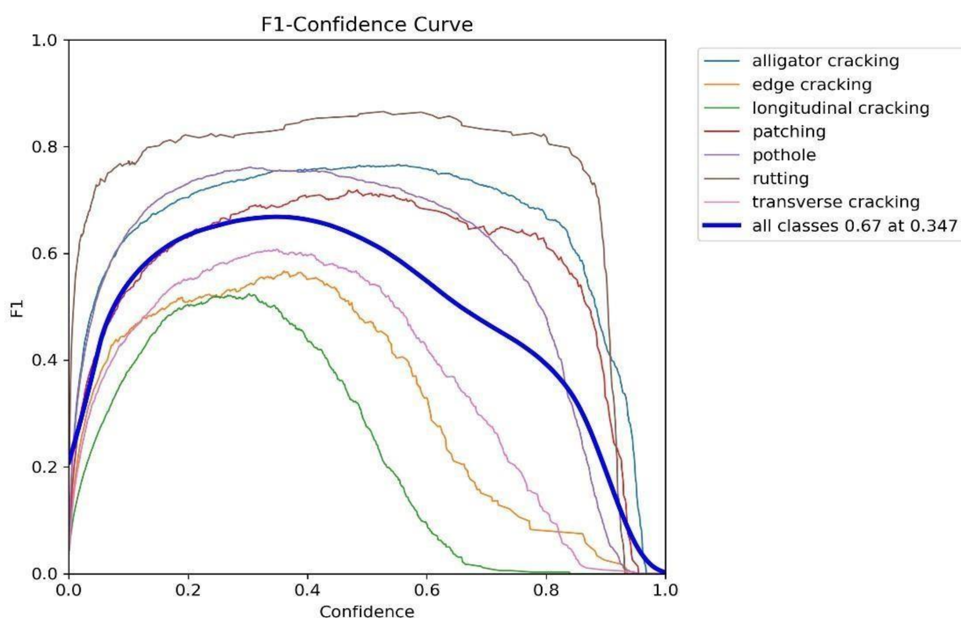



Fig 4.9: F1-Confidence curve for Case 1

### F1-Confidence Curve Analysis

Figure 4.3.2 presents the F1-Confidence Curve for all defect classes. The F1-Confidence Curve helps to determine how accurately the model detects and classifies defects at different confidence levels. The best overall performance was achieved at a confidence threshold of 0.347, with a mean F1-score of 0.67, indicating a good balance between precision (correct detections) and recall (missed detections).

Among all the pavement defect types, rutting recorded the highest F1-score, maintaining values above 0.8 across a wide confidence range. This means the model was highly reliable in detecting rutting defects. Alligator cracking, potholes, and patching also showed strong F1 performance, proving that the model effectively learned their distinct visual patterns. However, edge cracking and longitudinal cracking had lower F1-scores. This suggests that the model found it more difficult to differentiate these defect types, possibly because they share similar shapes and textures or because of background noise in the images.

The thick blue curve on the graph, which represents the performance of *all classes combined*, indicates the model's optimal confidence threshold, where detection accuracy was maximized across all pavement defect categories.

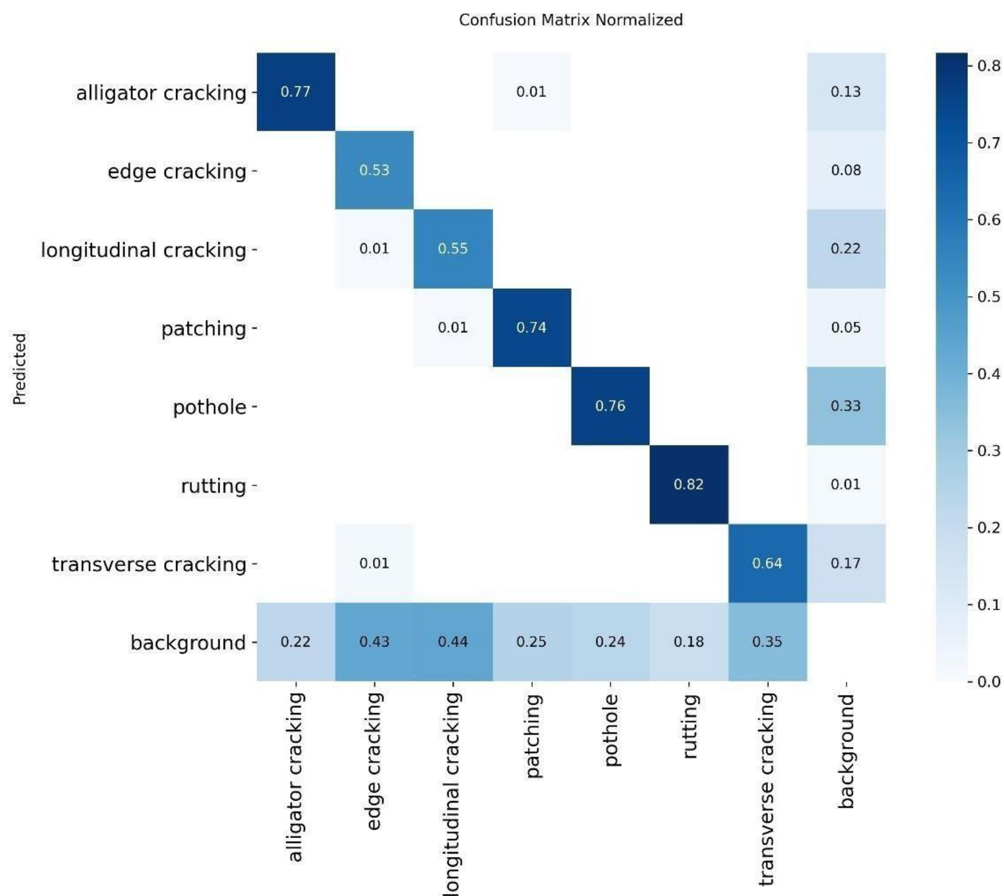



**Fig 4.10:** Normalized confusion matrix for Case 1

The model demonstrates strong classification performance for rutting (0.82), pothole (0.76), and alligator cracking (0.77). These high values along the diagonal show that the model effectively distinguishes these defect types from others due to their distinct visual features such as depth and texture irregularities.

Moderate detection accuracy is observed for patching (0.74) and transverse cracking (0.64), while edge cracking (0.53) and longitudinal cracking (0.55) show relatively lower accuracy. This misclassification trend may result from the visual similarity between edge and longitudinal cracks, as both exhibit linear patterns along the pavement surface.

### 4.2.2 Case 2: Learning Rate 0.01, Batch Size 64, Epochs 100

During the second training phase, the model was trained again using a moderate learning rate (same as in the first phase) and a suitable batch size. As the training progressed, the model slowly improved and became more stable, with the total loss steadily reducing after completing 100 training rounds (epochs). This shows that the model was learning effectively and getting better at detecting pavement defects.

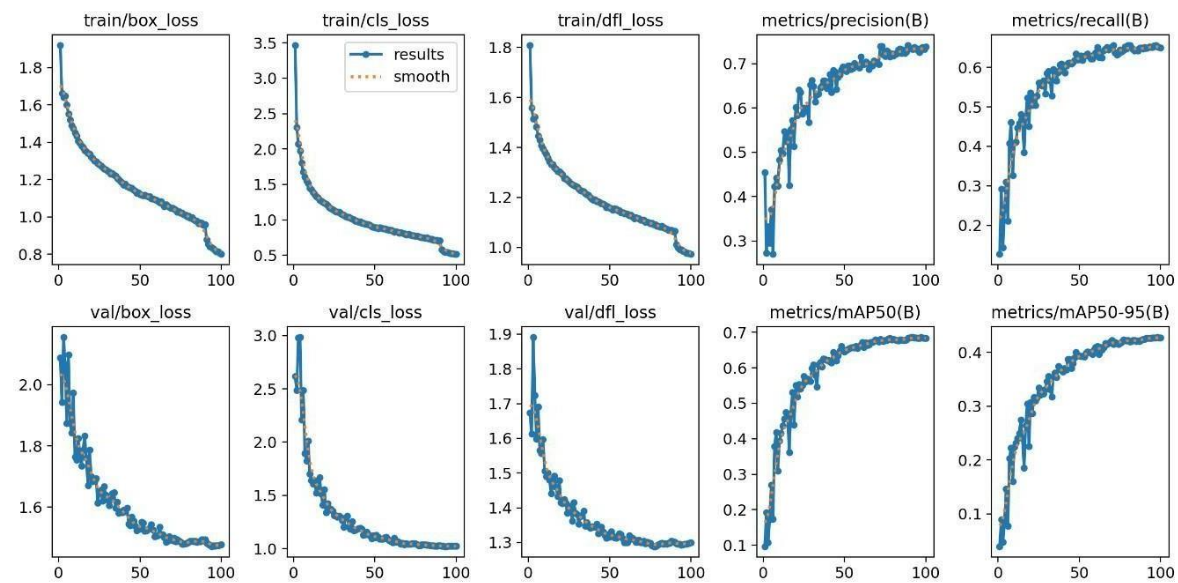



**Fig 4.11:** Training loss and mAP curves for Case 2

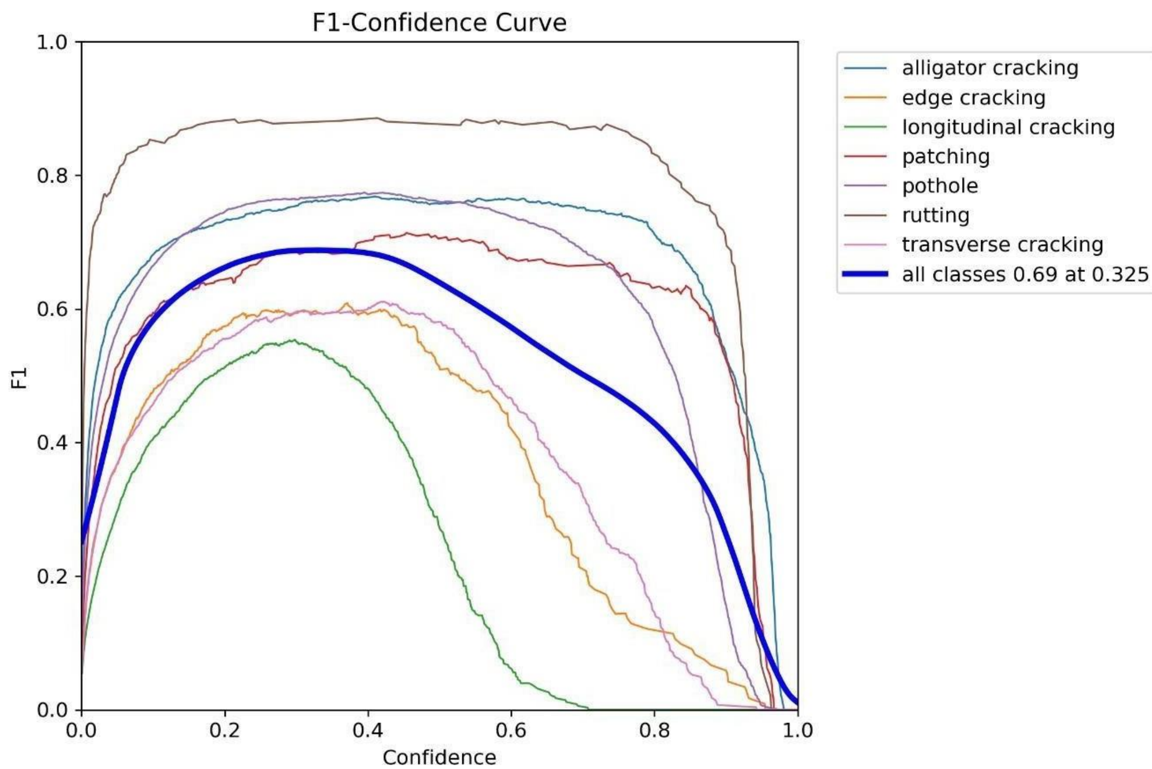



**Fig 4.12:** F1-Confidence curve for Case 2

**F1-Confidence Curve Analysis**

The F1-Confidence curve shows how well the model balances accuracy and consistency in detecting pavement defects at different confidence levels. The best F1 score obtained was 0.69 at a confidence threshold of 0.325, which means the model performed best when it was about 32.5% confident in its predictions. This curve also helps to identify which pavement defects were detected more accurately and which ones posed challenges based on their visual appearance.

The model showed its strongest performance in detecting rutting and alligator cracking, as these defects have clear and distinct visual characteristics such as depth variations and noticeable surface irregularities. These unique features made it easier for the model to recognize and classify them correctly during detection.

However, the model found it more difficult to identify edge cracking and longitudinal cracking, which are typically long, thin, and less visually prominent. These types of cracks often blend into the surrounding pavement surface, making them harder for the model to distinguish clearly. As a result, they were sometimes misclassified or missed entirely during detection.

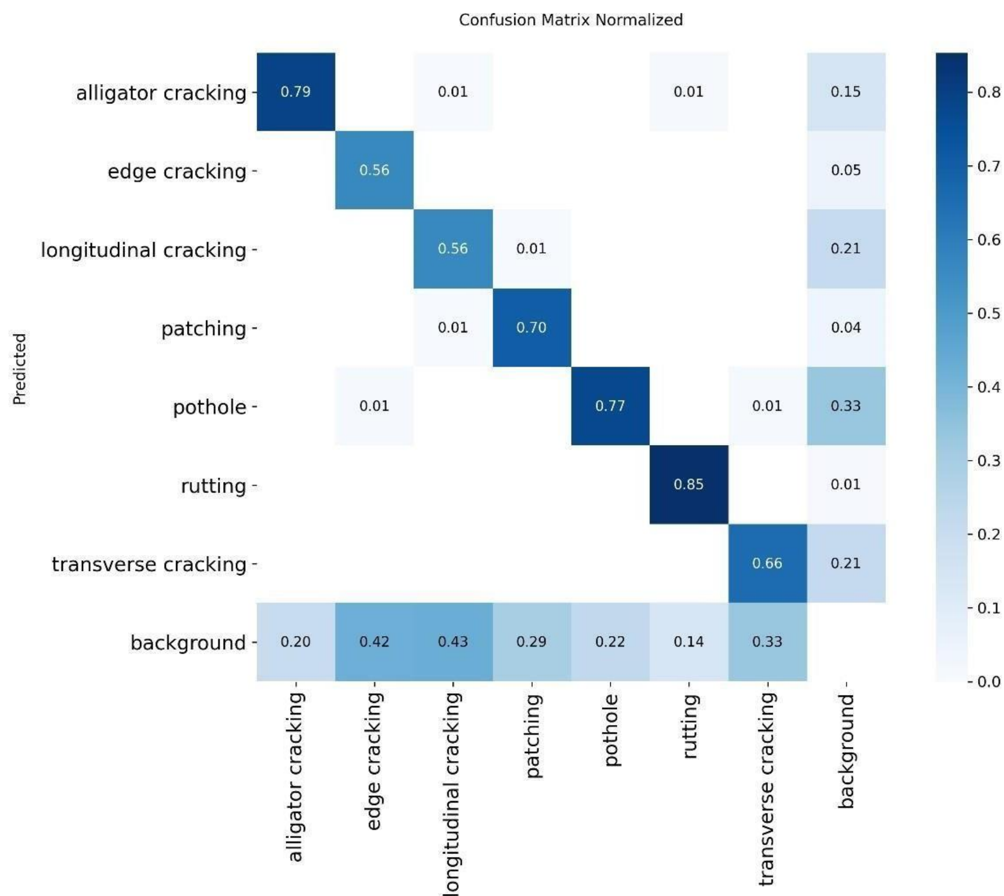



**Fig 4.13:** Normalized confusion matrix for Case 2

In the second training phase, the model showed improved ability in correctly identifying certain pavement defects. It performed very well in detecting rutting (0.85), potholes (0.77), and alligator cracking (0.79). These high scores mean the model could easily tell these defects apart from others because they have clear and unique features like depth, rough texture, or irregular surface patterns that stand out in road images.

The model had moderate accuracy for patching (0.70) and transverse cracking (0.66), meaning it recognized them fairly well but not as perfectly as the first group. However, its accuracy dropped for edge cracking (0.56) and longitudinal cracking (0.56). These two types of cracks often look alike because both forms long, thin lines on the pavement surface, which can confuse the model and lead to some misclassifications.

### 4.2.3 Case 3 and 4: Learning Rate 0.001, Batch Size 64, Epochs 100 and 200

In the third and fourth training phases, the learning rate was reduced by 10% compared to the first phase, while the batch size remained the same. This adjustment allowed the model to learn more carefully and steadily. As the training progressed through 100 and 200 epochs, the model showed gradual improvement, with a consistent decrease in total loss, meaning it made fewer errors and became more accurate in detecting pavement defects.

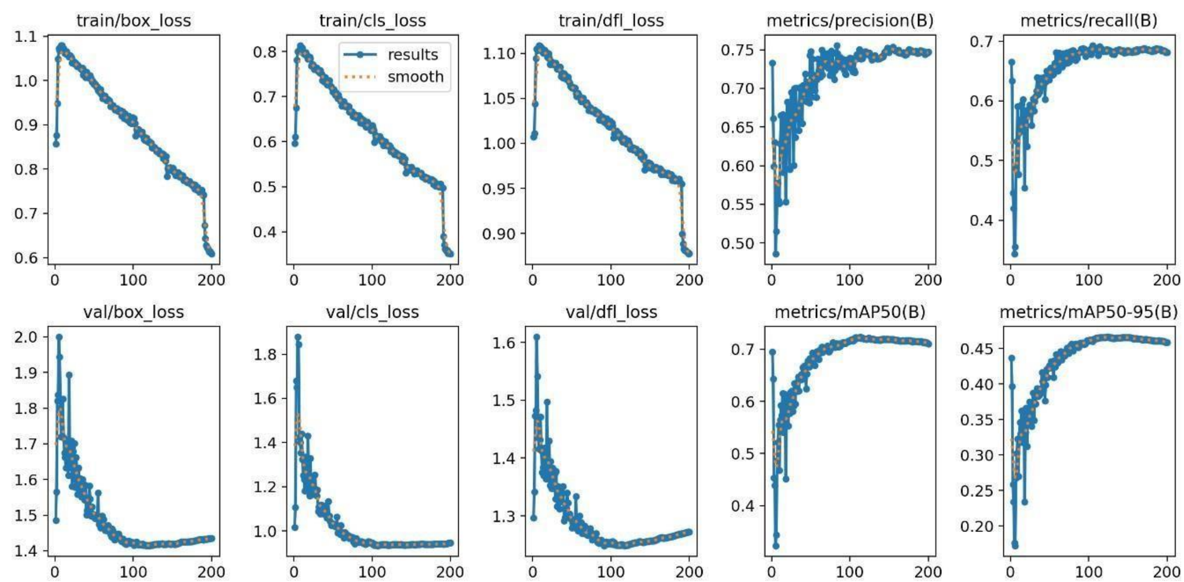



**Fig 4.14:** Training loss and mAP curves for Case 4

Throughout the third and fourth training phases, both the training loss and validation loss continued to decrease steadily, showing that the model was learning well and performing consistently on both the training and test data. The small difference between the two losses means the model did not overfit it didn't just memorize the training data but learned to recognize real pavement defects effectively.

By around the 150th epoch, the loss curves became almost flat, showing that the model had reached a stable learning point (convergence).

Also, performance measures such as precision, recall, and mean Average Precision (mAP50 and mAP50–95) improved sharply in the early stages of training and later became stable near their highest values.

This steady pattern indicates that the training process was well-optimized, and the model performed consistently across all detection tests, accurately identifying different pavement defects while maintaining a good balance between learning and generalization.

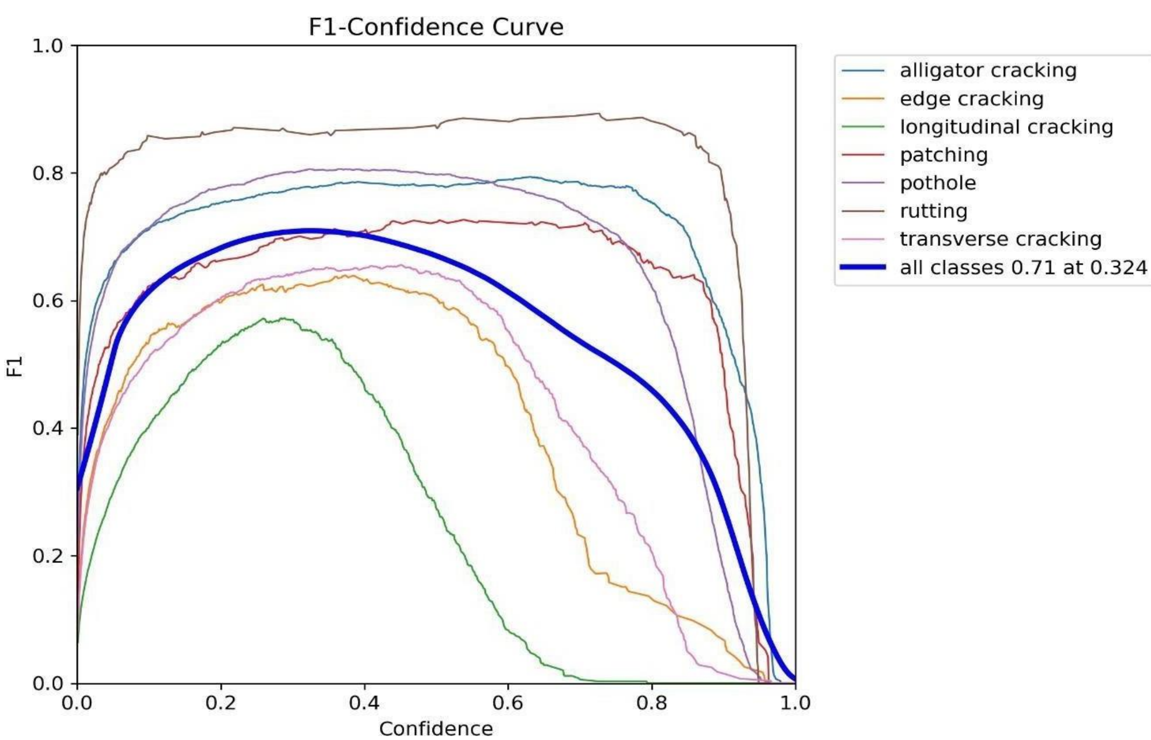



**Fig 4.15:** F1-Confidence curve for Case 4

The F1-Confidence Curve shows how well the model detects pavement defects at different confidence levels. The model reached its best F1 score of 0.71 at a confidence threshold of 0.324, meaning it achieved a good balance between precision (correctly identifying actual defects) and recall (detecting all existing defects).

Throughout all training stages, the model performed best on rutting, pothole, and alligator cracking, as these defects have distinct visual features such as depth, roughness, or irregular patterns that make them easier for the model to identify.

However, edge cracking and longitudinal cracking had lower F1 scores, showing that the model found it more challenging to detect these thin and elongated cracks, especially when they blended with the pavement texture or lighting. Patching and transverse cracking performed fairly well, maintaining average detection accuracy compared to the top-performing classes

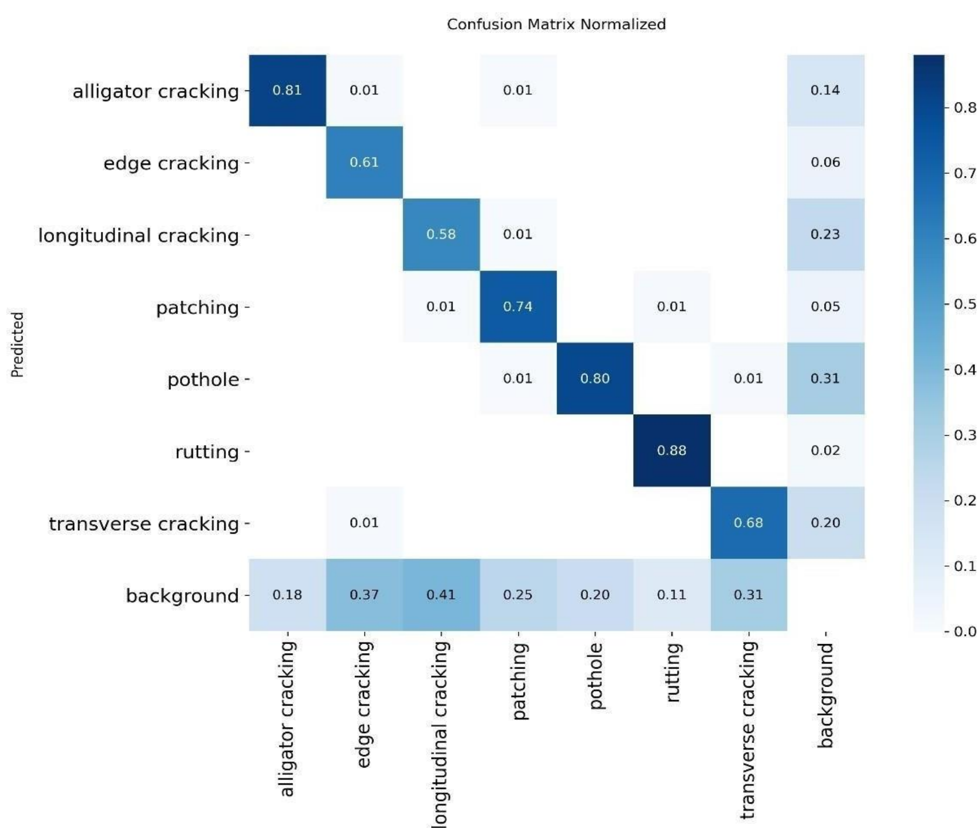


**Fig 4.16:** F1-Confidence curve for Case 4

The Normalized Confusion Matrix shows how well the model correctly identified each type of pavement defect, with the diagonal values representing how accurately each defect was detected (called recall).

From the analysis, the model performed best in detecting rutting, achieving a recall of 0.88, which means it correctly identified rutting defects most of the time. Similarly, it achieved high recall values for alligator cracking (0.81) and potholes (0.80), showing that the model could reliably detect these defects because of their clear visual features, such as depth, roughness, and irregular surface patterns.

However, the model's performance reduced for patching (0.74) and transverse cracking (0.68), and it performed poorest for edge cracking (0.61) and longitudinal cracking (0.58). These two defects were harder for the model to detect because they appear as thin, continuous lines that often blend with the pavement surface or shadows, making them less distinct.

A major observation across all defect types was confusion with the background. For instance, 41% of actual longitudinal cracks and 37% of edge cracks were mistakenly classified as background, meaning the model sometimes failed to recognize them as real cracks. Likewise, the background itself was often misidentified as cracks, showing that the model sometimes struggled to separate faint surface marks or discolorations from true pavement defects.

The model showed strong detection for major defects like rutting and potholes, but it needs improvement in detecting fine cracks and distinguishing subtle surface details from the background.

### 4.3 Model Inference and Qualitative Testing

To confirm how well the trained model performs in practical situations, it was tested using new pavement images that were not part of the training or validation data. These images were collected directly from the study areas in Benin City, showing actual road conditions with different types of surface defects.

During this testing (inference) stage, the model analyzed each image to detect, locate, and classify pavement distresses, such as potholes, cracks, and rutting. This step helped verify whether the model could correctly identify defects when exposed to different conditions, such as changes in lighting, pavement color, or camera angle.

The outcome of this phase demonstrated that the model was not just memorizing patterns from the training data but could also recognize and label pavement defects accurately in operational environments, proving its practical reliability and field readiness for pavement defect detection.

#### 4.3.1 Inference Parameters Settings

The final trained model, saved as best.pt, was selected as the optimal version after 200 epochs of training with a learning rate of 0.001. This model was used for the inference stage to evaluate its ability to detect and classify pavement defects on new images.

The inference process was carried out using a set of carefully chosen parameters that guided how the model made its predictions. The parameters, their corresponding values, and the rationale for each selection are presented in Table 4.3.1 below.

Table 4.3: Inference Parameter

| Parameter | Value | Rationale |
|---|---|---|

| | | |
|---|---|---|
| Image Size | 640 | Must match the input size used during training to maintain feature integrity. |
| Confidence Threshold | 0.50 | A moderate threshold chosen for balancing precision and recall in a practical deployment setting. (Note: |
| | | The global peak F1 was at 0.324, but 0.50 is often used for higher confidence.) |
| IOU Threshold | 0.45 | Standard value for Non-Maximum Suppression (NMS) to eliminate redundant, overlapping bounding boxes while retaining accurate, distinct detections. |

**Model Predictions**



Fig 4.17: Pothole detected with a precision Level of 87%

Fig 4.18: Pothole detected with a precision of 83%


Fig 4.19: Alligator Crack detected with 80%

Precision value

### 4.4.2 Qualitative Results and Observations

The inference results on the new study area images yielded the following key qualitative observations, showing bounding boxes and confidence scores for detected distresses:

1. **High-Confidence Detections (Rutting, Alligator Cracking, Potholes):**

The model showed very strong detection ability for clearly visible pavement defects such as rutting, alligator cracking, and well-defined potholes. It assigned high confidence scores above 0.80 and accurately drew bounding boxes around these defects, meaning it could correctly identify their positions on the pavement images.

This result supports the earlier findings from the confusion matrix, where these same defect types achieved high recall values (≥ 0.80) confirming that the model consistently recognized them whenever they appeared in the dataset.

2. **Performance on Linear Cracks (Edge and Longitudinal):**

The model had the most difficulty detecting edge cracking and longitudinal cracking. At the

0.50 confidence threshold, it often failed to identify some parts of these narrow cracks, resulting in missed detections (false negatives). This agrees with their low recall values ($\leq$ 0.61) observed earlier.

Even when the model detected these cracks, the bounding boxes it drew were not always accurate they sometimes covered extra parts of the pavement instead of the exact crack area. This shows that the model struggled to clearly define the boundaries of these thin and continuous crack patterns.

3. **Threshold Impact and Background Ambiguity:**

When the confidence threshold was increased to 0.50, the model became more selective in making predictions. This helped to reduce false positives that is, it made fewer mistakes of identifying normal pavement areas as cracks or defects compared to when it operated at the peak F1 threshold of 0.324.

However, there was still a challenge in clearly separating linear cracks (like edge and longitudinal cracking) from the background surface. Because these cracks often blend with the pavement texture, the model tended to be cautious, choosing to skip uncertain detections rather than risk wrongly labeling normal pavement as damaged.

4. **Overall Localization:**

For all defect detections made at a confidence threshold above 0.50, the model produced welldefined and accurately placed bounding boxes, clearly marking the areas affected by pavement damage. This shows that the training process was effective in teaching the model how to identify and outline the exact extent of visible defects on the pavement surface.

The qualitative testing results align with the quantitative performance metrics, showing that the model performed very well in detecting clear and distinct distress types such as rutting and potholes. However, it showed slightly lower confidence and precision when identifying faint or narrow linear cracks, indicating that while the model is strong overall, it still faces challenges in consistently detecting subtle crack patterns at the 0.50 inference threshold.

# CHAPTER FIVE

## CONCLUSIONS AND RECOMMENDATIONS

### 5.1 CONCLUSION

This research successfully applied deep learning techniques to the detection of pavement defects using the YOLOv8 model. By integrating data collected from the Edo State Ministry of Works, Diarsa Global Consulting Firm, field surveys within Benin City, and publicly available datasets, a robust and diverse dataset was developed. The preprocessing and annotation processes ensured high-quality input for model training, enabling accurate defect recognition across different pavement conditions.

The trained YOLOv8s model demonstrated strong detection performance, particularly for distinct distress types such as rutting, alligator cracking, and potholes, achieving high precision and recall values. Although minor challenges were observed in identifying subtle linear cracks like edge and longitudinal cracking, the overall model performance showed reliable generalization and adaptability to varying lighting and environmental conditions. This indicates that the model can serve as a dependable tool for automated pavement condition monitoring.

The study confirms that machine learning, particularly deep learning models like YOLOv8, can significantly enhance road maintenance practices by enabling faster, more objective, and cost-effective pavement defect detection.

### 5.2 RECOMMENDATION

Future research should focus on expanding the dataset by collecting more high-resolution images from different cities, pavement types, and weather conditions. Increasing the quantity and diversity of images will help improve the model's ability to detect subtle and complex defect types, particularly linear cracks.

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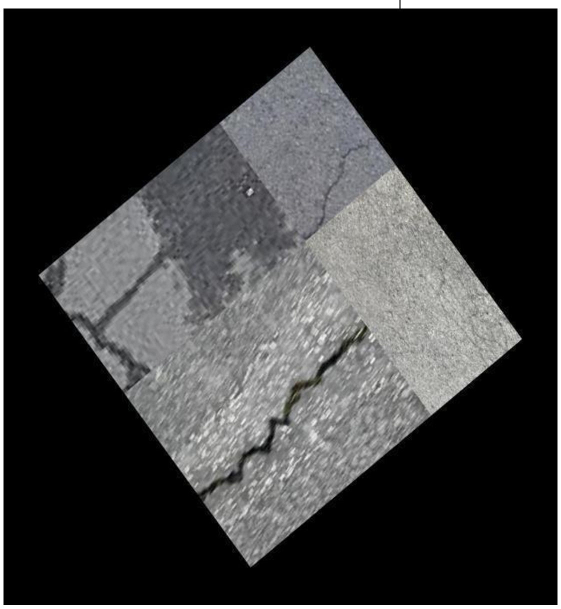
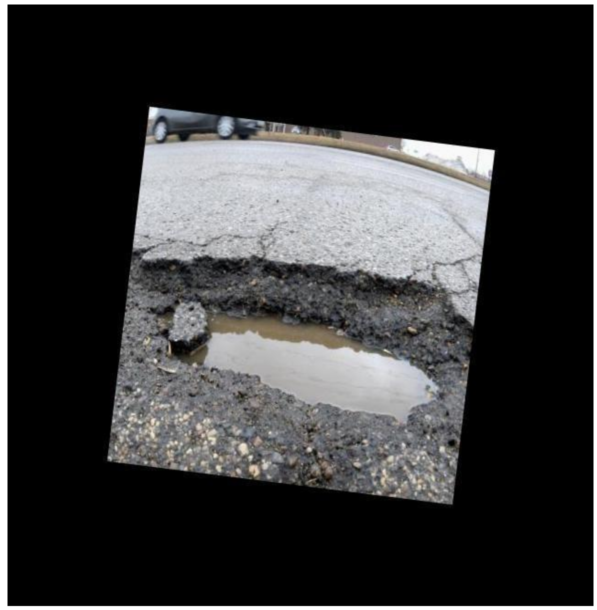
# APPENDIX

APPENDIX A

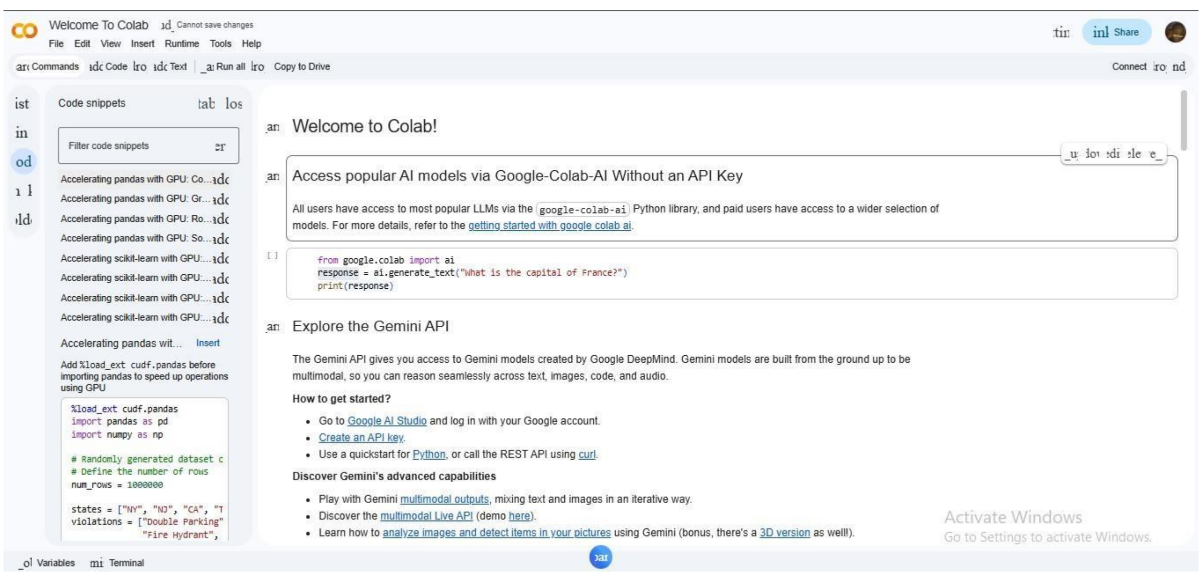
Pavement defects samples





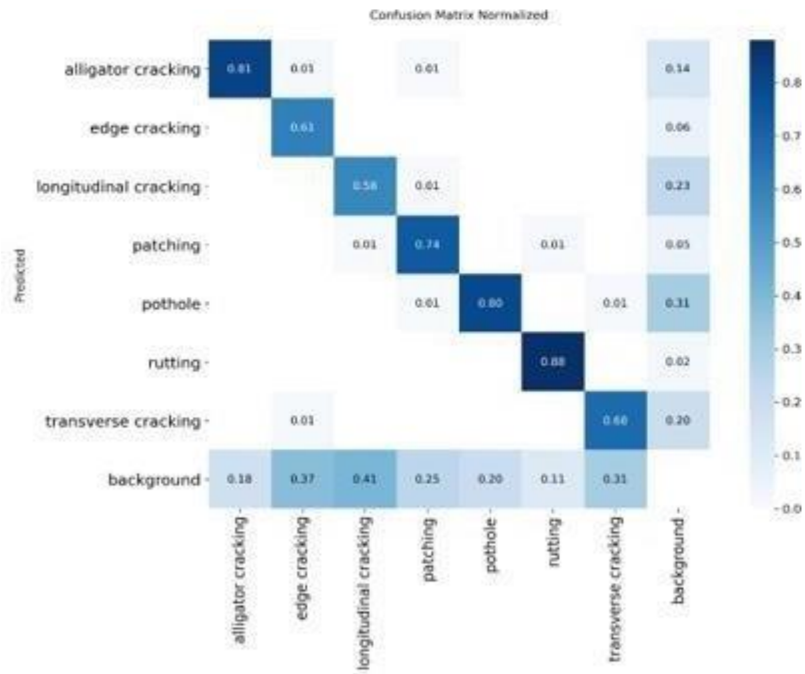
APPENDIX B

Google Colab




APPENDIX C

F1-Confidence curves




APPENDIX D

Inference Results



APPENDIX E

Sample Code – training Pipeline execution

```
import os
import cv2
import numpy as np
import matplotlib.pyplot as plt
from ultralytics import YOLO
import torch
print('CUDA available:",
torch.cuda.is_available())
print("GPU DEVICE:", torch.cuda.get_device_name(0) if
torch.cuda.is_available() else "No Device")
```