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Development of a Framework for Identifying Asphalt Pavement Cracking Distresses Using Machine Learning

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California State University Transportation Consortium

CALIFORNIA STATE UNIVERSITY Chico

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Development of a Framework for Identifying Asphalt Pavement Cracking Distresses Using Machine Learning

DingXin Cheng, PhD, PE

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16. Abstract Asphalt pavement cracking is one of the most critical distresses affecting pavement performance and service life. When pavement deteriorates, it can lead to safety hazards, higher vehicle maintenance costs, and expensive repairs for cities and states—making early detection essential for everyone who relies on the roadway system. To address this challenge, the research team developed a prototype cracking identification system that integrates a customized machine learning model with computer vision algorithms. High-resolution images collected from drones or ground-based cameras are processed within the system to automatically detect and classify major cracking types. The core of the framework utilizes the You Only Look Once (YOLO) architecture, which enables fast detection and accurate localization of cracking distresses. Experimental results demonstrate that the model achieves over 80% accuracy across multiple crack categories. In addition to detection efficiency, the system emphasizes usability, providing an effective tool for transportation agencies to support pavement evaluation and management. This innovative approach represents a step toward more automated, reliable, and scalable pavement condition assessment, which supports safer, more cost-effective transportation systems.		
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Executive Summary

Cracking is one of the most prevalent and detrimental distresses in asphalt pavements, with direct consequences for structural integrity, ride quality, safety, and long-term maintenance costs. If not detected and treated early, cracks can propagate rapidly, leading to costly rehabilitation and reduced service life. Conventional visual surveys remain the standard practice for many agencies, but they are inherently labor-intensive, time-consuming, and prone to inspector subjectivity. These limitations have motivated increasing research into automated detection methods, particularly those leveraging artificial intelligence and computer vision.

This study presents a prototype asphalt pavement cracking identification system that integrates a customized deep learning model with image-processing algorithms. The detection framework is built on the You Only Look Once (YOLO) architecture, chosen for its ability to simultaneously achieve high detection accuracy and fast inference speed. The model was trained using a dataset of high-resolution pavement images annotated across multiple distress categories, including longitudinal, transverse, block, and alligator cracking. To improve robustness under variable conditions, extensive data augmentation was applied, accounting for changes in illumination, surface texture, and crack severity.

Performance evaluation shows that the trained model achieves over 80% mean average precision (mAP) across major crack categories. Inference testing demonstrates that the system can process images at fast rates, enabling deployment with drone-based surveys or vehicle-mounted imaging platforms. Beyond detection, the system provides pixel-level localization and overlays bounding boxes directly on images, facilitating automated mapping and quantitative condition assessment.

The results indicate that deep learning-based detection can deliver objective, consistent, and scalable assessments of pavement conditions, surpassing the limitations of manual surveys. Future research will expand the dataset to include fine and sealed cracks, optimize the model architecture for lightweight mobile deployment, and integrate the system into pavement management platforms for network-level implementation.

1. Introduction

The deteriorating condition of road infrastructure in the United States remains a critical issue, with many highways and local roads suffering from aging materials, increased traffic loads, and insufficient maintenance. According to the American Society of Civil Engineers (ASCE), nearly 40% of public roadways are in poor or mediocre condition, contributing to higher vehicle operating costs, safety risks, and traffic congestion (ASCE, 2021). In urban areas, potholes and pavement distress are particularly prevalent, with studies linking poor road conditions to increased accident rates and delayed emergency response times (TRIP, 2023)

California's road infrastructure is still in urgent need of rehabilitation and strategic investment, as evidenced by the state's "D" grade in the 2021 Report Card for America's Infrastructure (ASCE, 2021). This poor rating reflects widespread issues such as deteriorating pavements, congestion, and insufficient maintenance—problems that directly impact safety, commute times, and economic productivity. With about 50% of California's roads rated in poor or mediocre condition (California Department of Transportation, 2022), the state must prioritize modernization efforts to prevent further decline. Experts warn that without immediate action, California could face $14 billion in additional vehicle repair costs and lost time by 2030 (TRIP, 2023). To address this crisis, policymakers must implement sustainable funding solutions—such as increased gas tax allocations or mileage-based user fees—while adopting data-driven asset management systems to optimize repairs (GAO, 2025). Strengthening California's roads is not just a logistical necessity but a critical step in safeguarding public safety, supporting commerce, and ensuring long-term resilience against climate-driven stressors.

Accurate pavement condition assessment is critical for determining appropriate funding levels and selecting optimal maintenance treatments, yet current methodologies face significant limitations. While state agencies such as Caltrans employ automated systems with specialized survey vehicles for highway networks, most local jurisdictions can't afford the costs of the advanced survey methods and still rely on manual visual surveys conducted by field crews—a process prone to subjectivity, inefficiency, and high human error rates. Although the exact average human error rate is not available, it is well known that errors can come from subjectivity, a lack of standardized training, and the labor-intensive nature of the work. This data gap creates substantial risks: underreported distress leads to deferred maintenance, while overestimation wastes limited budgets on unnecessary treatments (Smith et al., 2020). To address these challenges, we propose implementing a new automated distress identification system at an affordable cost.

Artificial Intelligence (AI) has emerged as a transformative tool for pavement condition assessment, leveraging computational algorithms and machine learning (ML) to analyze complex data patterns (Majidifard et al., 2020a). Recent advancements in automatic data acquisition, computer vision, and deep learning (DL) have enabled AI systems to automatically identify and classify pavement distress with increasing accuracy (Hou et al., 2021; Xu & Zhang, 2022). Although the AI/ML approach may reduce the labor workforce in pavement condition survey, these technologies offer three key advantages: (1) automation of labor-intensive data collection, (2) high-fidelity modeling when trained on robust datasets, and (3) real-time monitoring capabilities (Guerrieri & Parla, 2022). However, significant challenges remain, particularly in data availability—AI models require large, high-quality datasets encompassing diverse distress types (e.g., cracks, potholes, rutting) and severity levels to achieve reliable classification (Sholevar et al., 2022). To address these limitations, we propose an integrated AI-powered system combining a low-cost video camera setup and a large set of roadway conditions in California.

1.1 Background

Asphalt pavement distress is a critical factor influencing road safety, ride quality, and maintenance planning. Traditional methods for evaluating pavement condition—such as manual inspections and in-vehicle surveys—are often labor-intensive, time-consuming, and prone to subjective inconsistencies. With the increasing demand for scalable and efficient pavement management systems, machine learning (ML) has emerged as a powerful tool to automate the detection and classification of various pavement distresses.

Machine learning, especially deep learning techniques such as convolutional neural networks (CNNs), enables automated analysis of pavement images to identify surface anomalies such as cracks (longitudinal, transverse, alligator), potholes, raveling, bleeding, and patches. By training on large datasets of labeled images, ML models learn to distinguish subtle visual patterns associated with different types of distress.

The integration of ML into pavement assessment systems offers several advantages:

- Scalability: Automated models can process vast amounts of image data from road networks efficiently.
- Consistency: Machine learning reduces human subjectivity, improving the reliability of assessments.
- Speed: Real-time or near-real-time analysis enables timely maintenance interventions.

Recent advancements in computer vision, data augmentation, and edge computing have further enhanced the applicability of ML models in real-world pavement monitoring scenarios. Ongoing research also explores combining ML with remote sensing, drone imaging, and 3D surface reconstruction to achieve higher accuracy and robustness in distress detection.

Historically, pavement distress identification depended on manual inspections, where technicians evaluated road conditions using standardized metrics such as the Pavement Condition Index (PCI). While systematic, these methods were labor-intensive, subjective, and hazardous, often yielding inconsistent results due to human variability (National Academies of Sciences, Engineering, and Medicine, 2024). Early automation efforts, including systems such as GERPHO and Komatsu, employed 2D imaging and conventional image processing techniques (e.g., Sobel filters, wavelet transforms) but faced limitations in handling complex real-world scenarios, necessitating manual feature extraction (Majidifard et al., 2020). The emergence of machine learning (ML), especially deep learning (DL), marked a paradigm shift by enabling direct feature learning from raw data. Modern ML approaches address the shortcomings of traditional methods through scalable data processing, noise resilience, and real-time capabilities—key advantages for cost-effective infrastructure management (Sensors Journal Review, 2022).

Machine learning has transformed asphalt pavement distress identification from subjective visual inspections to high-precision automated systems. Innovations in deep learning architectures, coupled with multimodal data fusion, enable robust detection across diverse scenarios.

1.2 Organization of the Report

This report is organized into the following sections: Section 1 outlines the problems of cracking in asphalt pavements and explains how AI technologies might be used to solve these problems. Advantages of ML include scalability, consistency, and speed. Section 2 discusses the objectives of the study. Section 3 discusses ASTM standards, including types of pavement distresses. This section also discusses artificial intelligence and machine learning. Section 4 presents the results and analysis. Finally, Section 5 draws conclusions and makes recommendations.

2. Objective

The objective of this research is to develop an automated pavement distress identification method using machine learning and computer vision. The approach will leverage drone-acquired imagery and high-resolution video recording to collect comprehensive visual data of road surfaces in California. This method aims to replace the current inefficient process of using manual inspection for detecting distresses such as various types of cracking. By applying advanced computer vision techniques similar to those used in medical imaging analysis (e.g., MRI, CT scans), the research seeks to accurately identify and quantify pavement distresses. The anticipated outcome is a system that improves accuracy, productivity, and cost-efficiency over existing pavement condition assessment techniques.

3. Research Approach

The research team has developed a prototype of an asphalt pavement cracking identification model with the aim of establishing an effective pavement condition evaluation process that will contribute to automatically assessing pavement conditions, which can lead to better road assessment and treatment recommendations.

3.1 Standardized Frameworks for Asphalt Pavement Distress Identification

The accurate assessment of asphalt pavement distress hinges on standardized methodologies that ensure consistency across agencies and technologies. The ASTM D6433 standard provides the foundational framework for Pavement Condition Index (PCI) calculations, establishing uniform metrics for distress severity and density quantification across road networks (ASTM, 2023). At the federal level, the Federal Highway Administration's Long-Term Pavement Performance (LTPP) Distress Identification Manual serves as the definitive taxonomy, cataloging 25+ distress types—from alligator cracking to bleeding—with standardized photographic references and severity scales. This manual enables longitudinal data comparability across U.S. states, crucially supporting machine learning training datasets (FHWA, 2020).

Regional standards further refine these protocols: California's Caltrans Automated Distress Manual operationalizes FHWA principles for technology-driven surveys, specifying tolerances for crack width measurements (±1mm) and rutting measurements (Caltrans, 2022). Similarly, the MTC Asphalt Pavement Distress Identification Manual tailors evaluation criteria to the climatic and material conditions, emphasizing cracking, distortion, patching, rutting, raveling, and weathering (Metropolitan Transportation Commission, 2021). Collectively, these standards reconcile field practicality with automated analysis needs, ensuring distress classifications remain reproducible whether performed by human inspectors or AI algorithms. The following are some common standards for asphalt pavement distresses.

3.1.1 ASTM International

ASTM D6433 is a standard practice for evaluating the condition of roads and parking lots. It uses the Pavement Condition Index (PCI) method. The PCI has a numerical rating from 0 to 100, where 100 represents a pavement in perfect condition. The standard provides a detailed methodology for conducting visual surveys to identify and measure 20 different types of distress for asphalt pavements. These distresses are key to calculating the PCI. Here is a summary of the AC (Asphalt Concrete) pavement distresses typically included in ASTM D6433:

- Cracking: This is one of the most common and critical distress types. Cracking is further categorized into different types based on its pattern and cause:

    - Alligator Cracking (Fatigue Cracking): A series of interconnected cracks that form a pattern resembling alligator scales. It is caused by repeated traffic loading and indicates structural failure of the pavement.

    - Block Cracking: Cracks that divide the pavement into large, rectangular blocks. This is often caused by the aging and shrinkage of the asphalt binder.

    - Edge Cracking: Cracks that run along the outer edge of the pavement, typically within 1 to 2 feet of the edge. It is often caused by a lack of support at the pavement edge.

    - Longitudinal and Transverse Cracking: Cracks that run parallel (longitudinal) or perpendicular (transverse) to the pavement's centerline. These can be caused by a variety of factors, including thermal changes, poor construction, or reflective cracks from underlying layers.

    - Slippage Cracking: Crescent-shaped cracks caused by a lack of a strong bond between the surface layer and the underlying pavement layer.

- Surface Defects: These distresses are related to the surface texture and material of the pavement:

    - Bleeding: A film of asphalt on the pavement surface that creates a smooth, shiny, and potentially slick appearance.

    - Polished Aggregate: The aggregate on the pavement surface has become smooth under traffic, reducing skid resistance.

    - Raveling and Weathering: The progressive loss of asphalt and aggregate from the pavement surface, leaving a rough texture.

- Deformations: These are changes in the shape of the pavement surface:

    - Rutting: Depressions that form in the wheel paths of traffic. It is caused by the permanent deformation of the pavement layers.

    - Shoving: A localized, permanent deformation that creates a ripple effect, often occurring at intersections where vehicles stop and start.

    - Depressions and Sags: Localized areas of the pavement that are lower than the surrounding surface, often caused by settlement of the underlying material.

    - Bumps and Sags: Localized bulges or dips in the pavement surface.

- Other Distresses:
    - Potholes: Bowl-shaped holes in the pavement surface, often caused by the breakdown of an existing crack or a localized area of distress.
    - Patching and Utility Cuts: Areas of the pavement that have been replaced or repaired. The condition of the patch itself is also evaluated.
    - Lane/Shoulder Drop-Off: A difference in elevation between the pavement and the shoulder.

The PCI calculation takes into account the type, severity (e.g., low, medium, or high), and extent (e.g., area or length) of each of these distresses to provide a single, comprehensive score for a given pavement section.

3.1.2 FHWA LTPP

The FHWA Long-Term Pavement Performance (LTPP) program has a comprehensive Distress Identification Manual (DIM) to ensure consistent data collection for its long-term study of pavement performance. While ASTM D6433 provides a framework for the Pavement Condition Index (PCI), the LTPP manual offers a more detailed and research-oriented approach to identifying and measuring pavement distress. The asphalt concrete (AC) portion of the LTPP manual is particularly thorough and serves as a key reference for many transportation agencies. The distresses are categorized and defined with specific criteria for measurement and severity levels.

Here is a summary of the 15 asphalt pavement distresses covered in the FHWA LTPP manual:

- Cracking:
    - Fatigue Cracking (Alligator Cracking): A network of interconnected cracks that form in areas of the pavement subjected to repeated traffic loads. It is a sign of structural failure. The manual specifies how to measure the area of the affected region and how to categorize the severity based on the crack pattern and spalling.
    - Block Cracking: Cracks that form a pattern of large, rectangular blocks. The manual distinguishes this from fatigue cracking by the size of the blocks and the fact that it is generally not load-associated.
    - Edge Cracking: Cracks that appear along the outer edge of the pavement, often due to a lack of shoulder support.

    - Longitudinal Cracking: Cracks that run parallel to the pavement's centerline. The manual further specifies if the cracking is in the wheel path or not, as this has different implications for the cause and severity.
    - Transverse Cracking: Cracks that run perpendicular to the pavement's centerline, typically caused by thermal changes and aging.
    - Reflection Cracking at Joints: Cracks in an asphalt overlay that mirror the pattern of underlying joints in a concrete pavement.
- Patching and Potholes:
    - Patch/Patch Deterioration: An area of pavement that has been replaced to repair a localized distress. The manual evaluates the condition of the patch itself, noting if it is in good or poor condition.
    - Potholes: Bowl-shaped holes in the pavement. The manual provides specific measurements for depth and area to determine severity.
- Surface Deformation:
    - Rutting: Longitudinal depressions that form in the wheel paths. The manual provides a method for measuring the depth of these depressions to determine severity.
    - Shoving: A localized, permanent deformation that creates a rippling effect in the pavement, often found at intersections or other areas with braking or accelerating vehicles.
- Surface Defects:
    - Bleeding: The presence of excess asphalt on the pavement surface, which can cause a smooth, shiny, and slick surface.
    - Polished Aggregate: The aggregate on the pavement surface has been worn smooth by traffic, which reduces skid resistance.
    - Raveling: The progressive loss of asphalt and aggregate from the surface, leaving a rough texture.
- Miscellaneous Distresses:
    - Lane-to-Shoulder Drop-Off: A difference in elevation between the main travel lane and the shoulder.

- Water Bleeding and Pumping: The expulsion of water and fine material from beneath the pavement through cracks and joints, which indicates sub-surface erosion and a potential structural problem.

The LTPP manual's approach is designed to provide detailed, quantitative data for engineering and research purposes, allowing engineers and researchers to better understand the causes and progression of pavement distress and to develop more accurate performance models.

3.1.3 Caltrans

The Caltrans Automated Pavement Condition Survey (APCS) Manual is a key document for how the California Department of Transportation systematically collects and analyzes pavement data across its state highway network. Chapter 3 specifically focuses on asphalt pavement distresses, their measurement, and reporting. Here is a summary of the key aspects of Chapter 3:

- Automated Data Collection: Caltrans has moved to an automated system to collect pavement condition data. This is done by specialized vehicles equipped with high-resolution cameras, inertial profilers, and laser systems that can capture data at highway speeds. This approach is intended to provide comprehensive, consistent, and safe data collection across the entire network.

- Pavement Distress Types: The manual defines a specific set of asphalt pavement distresses that are to be identified and measured by the automated system. While these often align with national standards, such as those from ASTM and FHWA, the manual provides Caltrans-specific definitions and criteria for severity and extent. Common distress types include:

  Cracking

  - Alligator Cracking (A and B): This is a fatigue-related distress characterized by a series of interconnected cracks that form a pattern resembling alligator scales. It indicates a structural failure of the pavement.

    - Alligator Cracking A: This refers to fine, hairline cracks. These cracks may not be fully interconnected and can be difficult to see with the naked eye from a moving vehicle. They are considered low severity and are often an early sign of fatigue failure. The manual specifies a crack width threshold for this category.

    - Alligator Cracking B: This represents a more severe stage where the cracks are fully interconnected, forming a well-defined pattern. The severity is determined by the degree of spalling (crumbling of the pavement edges along the cracks) and the width of the cracks. This indicates a more advanced structural failure and often requires more significant rehabilitation.

- Block Cracking: These are interconnected cracks that divide the pavement into rectangular or square blocks, typically ranging from 1 to 10 feet in size. Unlike alligator cracking, this is generally not caused by traffic loads but by the aging and shrinkage of the asphalt binder. The severity is often based on the average width of the cracks.

- Edge Cracking: These are crescent-shaped or hairline cracks that form along the outer edge of the pavement, often within 1 to 2 feet of the pavement edge. It is typically caused by a lack of support at the pavement edge or heavy loads close to the edge. The severity is determined by the crack width and the degree of spalling.

- Longitudinal Cracking: Cracks that run parallel to the pavement's centerline or laydown direction. The manual often distinguishes between cracks in the wheel path and those between the wheel paths. The severity is based on the crack width and whether there is spalling.

- Transverse Cracking: These are cracks that run perpendicular to the pavement's centerline. They are primarily caused by thermal stresses (e.g., shrinkage during cold weather). The severity is based on the crack width and the presence of spalling.

Other Distresses

- Pothole: A bowl-shaped hole in the pavement that extends through the surface layer. Potholes are typically formed by the breakdown of an existing crack or a localized area of distress. The manual specifies that a measurement of the area and depth of the pothole is necessary to determine its severity.

- Bleeding: The migration of excess asphalt binder to the pavement surface, creating a shiny, dark, and potentially slick surface. This can significantly reduce skid resistance. The severity is based on the extent of the area affected and the degree of shininess.

- Raveling: The progressive loss of asphalt binder and aggregate particles from the pavement surface, resulting in a rough, coarse texture. Raveling is caused by a poor mix, aging, or traffic wear. The severity is based on the degree of aggregate loss.

- Measurement and Severity: A critical part of the manual is its methodology for measuring the distresses. The automated system collects data that can be used to quantify the distress in terms of:

- Extent: The length or area of the distress. For example, a certain type of crack might be measured in linear feet, while block cracking might be measured in square feet.
- Severity: The manual defines different severity levels (e.g., low, medium, high) for each distress type. These levels are based on specific criteria such as crack width, rut depth, or the size and depth of a pothole.

- Data Reporting and Management: The data collected through the APCS is a critical input for Caltrans' Pavement Management System (PaveM). Chapter 3, along with other parts of the manual, outlines how the raw data from the automated survey is processed and aggregated.
    - The data is used to calculate various pavement condition indicators, which help Caltrans make informed decisions about maintenance and rehabilitation projects.
    - The manual provides the framework for generating reports, such as the State of the Pavement report, that summarize the condition of the state's highway network.

The APCS data is used for both internal management decisions and for reporting compliance with federal requirements, such as those from the Federal Highway Administration (FHWA).

3.1.4 MTC Asphalt Pavement Distress Identification Manual

The Metropolitan Transportation Commission (MTC) Pavement Condition Index (PCI) Distress Identification Manual for Flexible Pavements is designed to help users of the StreetSaver® Pavement Management Software (PMS) consistently identify pavement distresses. This manual is used to calculate the Pavement Condition Index (PCI) for flexible pavements and is derived from rating methods developed by the U.S. Army Corps of Engineers Construction Engineering Research Laboratory (CERL).

Pavement Distresses and Severity Levels

The manual outlines 8 specific asphalt pavement distresses and provides criteria for their severity levels and measurement. The following is a summary of the distresses.

- Alligator Cracking – A series of interconnected cracks from fatigue failure of asphalt concrete under repeated traffic loading, usually in wheel paths.
    - Low Severity: Fine longitudinal hairline cracks with few interconnections; no spalling.
    - Medium Severity: Lightly spalled network of cracks forming a pattern.

- High Severity: Well-defined, spalled pieces; may rock under traffic. Potholes are recorded as high severity.

Measurement: Measured in square feet; if severities can't be separated, rate the whole area at the highest severity.

- Block Cracking – Interconnected longitudinal and transverse cracks dividing pavement into rectangles 1×1 ft to 10×10 ft. Caused by asphalt shrinkage and temperature cycling, not load.
    - Severity: Based on severities of component longitudinal and transverse cracks.
    - Measurement: Measured in square feet; low severity uncommon. Cannot be recorded in the same area as longitudinal/transverse cracks.
- Distortions – Localized abrupt upward/downward displacements, ridges, valleys, bumps, sags, or shoving caused by unstable materials, loss of support, or root growth.
    - Severity: Determined by ride quality in a sedan at posted speed; higher severity = rougher ride.
    - Measurement: Measured in square feet; record each distinct severity separately.
- Longitudinal and Transverse Cracking – Longitudinal cracks run parallel to the pavement centerline; transverse cracks run perpendicular. Caused by joint issues, asphalt shrinkage, reflective cracking, or edge support loss. Not normally load-related.
    - Low Severity: Non-filled <3/8 in wide or filled in good condition.
    - Medium Severity: Non-filled 3/8–3 in wide or filled with light random cracking nearby.
    - High Severity: Non-filled >3 in, or filled with surrounding medium/high random cracking, or with severe breakage.
    - Measurement: Measured in linear feet, with each severity recorded separately.
- Patching and Utility Cut Patching – Replaced or covered areas to repair pavement; utility cuts replace pavement for underground utility work. Always considered defects regardless of performance.
    - Severity: Based on roughness and condition of the patch surface.

- Measurement: Measured in square feet; different severities within a patch recorded separately. No other distress types are recorded within a patch.

- Rutting and Depressions – Ruts are wheel path depressions from permanent deformation in pavement or subgrade; depressions are localized low spots ("bird baths") from settlement or construction issues.
  - Severity: Based on mean rut depth measured with a 10 ft straight-edge.
  - Measurement: Measured in square feet; record separate areas for different severities.

- Raveling – Dislodging of coarse aggregate from the pavement surface due to issues such as low asphalt binder, poor mix quality, or compaction.
  - Medium Severity: >20 coarse aggregates lost per square yard and/or clusters missing.
  - High Severity: Surface rough, pitted, possibly missing completely in places.
  - Measurement: Measured in square feet; cannot be recorded with weathering in the same area.

- Weathering – Wearing away of asphalt binder and fine aggregate matrix from oxidation, compaction issues, low binder content, or erosion.
  - Severity: Based on the extent of binder/fine matrix loss and exposure of coarse aggregate.
  - Measurement: Measured in square feet; cannot be recorded with medium/high raveling in the same area.

3.2 Machine Learning Approach

In this research, a machine learning approach is used to identify the asphalt pavement distresses. Specifically, preliminary models have been developed for MTC's asphalt pavement distresses. Pavement distresses using other standards—such as ASTM, FHWA LTPP, and Caltrans—can be developed using a similar approach.

3.2.1 Artificial Intelligence

The integration of artificial intelligence (AI) technologies has redefined asphalt pavement diagnostics, merging sensing, analysis, and decision support into unified frameworks. Computer vision (CV), powered by convolutional neural networks (CNNs) and vision transformers (ViTs), automates high-accuracy distress detection—enabling fast crack identification at 1mm resolution from 4K imagery and 3D LiDAR point clouds (Majidifard et al., 2024). Utilizing these advances, machine learning (ML) algorithms (e.g., YOLO for object detection, U-Net for pixel-level segmentation) process multimodal data—including ground-penetrating radar and infrared thermography—to correlate surface anomalies with subsurface defects such as moisture delamination (FHWA, 2023). Beyond traditional ML, large language models (LLMs) such as GPT-4 and Llama-3 now enhance diagnostic interpretability: They generate natural-language inspection reports from CV outputs, align findings with standards such as ASTM D6433, and even recommend region-specific maintenance strategies by synthesizing climate, traffic, and material data. This AI ecosystem—spanning CV's perception, ML's pattern recognition, and LLM's contextual reasoning—creates closed-loop intelligence, reducing inspection costs while improving PCI prediction accuracy (National Academies, 2024).

3.2.2 Machine Learning

Machine learning is a branch of artificial intelligence that focuses on developing algorithms and models that enable computers to learn from data, identify patterns, and make predictions or decisions without being explicitly programmed for each task. It uses statistical and mathematical methods to improve performance as more data becomes available. It is widely applied in areas such as image recognition, natural language processing, recommendation systems, and autonomous systems. Machine learning often utilizes neural networks. The following are commonly used neural network architectures.

1. Artificial Neural Network (ANN)

   ANN is the foundational machine learning model inspired by how biological neurons work. It consists of layers of interconnected "neurons" (nodes) that transform input data into outputs through weighted connections and activation functions. Typically, it is used for general-purpose pattern recognition, regression, and classification when input features are already numerical. The limitation is that it does not inherently handle sequential or spatial data well without modifications.

2. Recurrent Neural Network (RNN)

   An RNN is a neural network designed to handle sequential data by having "memory" of previous inputs. It passes information from one step to the next in a sequence, allowing it to model time-dependent relationships. Variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) help with long-term dependencies. Typically, it is used in time-series forecasting, natural language processing, and speech recognition. The limitation is that it has slower training and can struggle with very long sequences despite LSTM/GRU improvements.

3. Convolutional Neural Network (CNN)

A CNN is a neural network specialized for processing grid-like data, such as images. It uses convolutional layers to scan local regions of an image with filters (kernels), detecting features such as edges, textures, and shapes, followed by pooling layers to reduce spatial size. It is often used for image classification, object detection, segmentation, and video analysis. It is excellent at capturing spatial hierarchies and patterns in images.

4. ResNet (Residual Network)

ResNet is a deep CNN architecture that solves the “vanishing gradient” problem by introducing skip connections (residual blocks). ResNet is an advancement that allows for the creation of much deeper and more effective CNNs. It allows the network to learn residual functions (differences from the input) instead of learning mappings from scratch, enabling much deeper networks without performance degradation. It is typically used in image classification, object detection, and as a backbone in many modern vision models. It forms the backbone for many advanced computer vision systems due to its depth and accuracy.

5. YOLO (You Only Look Once)

YOLO is a real-time object detection and (in later versions) segmentation algorithm. It processes the entire image in a single pass, dividing it into a grid and predicting bounding boxes and class probabilities for multiple objects simultaneously. It is typically used in real-time object detection in images or videos—such as detecting pavement cracks, potholes, or road signs.

3.2.3 Computer Vision

Computer vision is a field of artificial intelligence that enables computers to interpret and understand visual information from the world, such as images and videos (Szeliski, 2022). It uses algorithms and models to detect, classify, and analyze objects, patterns, and features, allowing machines to perform tasks such as image recognition, object tracking, and scene understanding, often mimicking or surpassing human visual perception in specific applications.

3.2.4 Large Language Model

A large language model (LLM) is an advanced type of artificial intelligence trained on vast amounts of text data to understand, generate, and reason with human language. It uses deep learning, typically transformer architectures, to perform tasks such as answering questions, writing text, translating languages, and summarizing information.

LLMs can still play a supporting role in pavement distress prediction by interpreting and explaining results from vision models and combining text data with predictions (e.g., merging sensor readings, project notes, and model outputs into summaries).

3.3 Use Machine Learning to Identify and Measure Pavement Distresses

Machine learning, a pivotal component of artificial intelligence, has made significant strides in recent years, transforming the way we approach and solve many complex problems. The development of a trained machine learning model to identify asphalt pavement distresses is a prime example of this advancement. By leveraging vast datasets and sophisticated algorithms, such a model can learn to recognize the characteristics of asphalt pavement cracking, differentiating them from other road anomalies (e.g., rutting and depression) or non-issues (e.g., shades) with remarkable accuracy. This streamlines the process of identifying necessary repairs and optimizes the allocation of resources, ensuring that maintenance efforts are directed where they are most needed. Furthermore, the automation of this task reduces reliance on human inspections, which can be subjective and inconsistent, thereby enhancing the overall efficiency of road maintenance operations.

Machine learning models offer significant cost savings by working non-stop, rapidly analyzing thousands of images, and adapting to new patterns—tasks that would be far more time-intensive and costly for human staff. What's more, these models continually improve through retraining and updates, delivering better performance over time and making them a game-changer for pavement management. This practical application showcases machine learning's potential to transform industries with intelligent, scalable, and sustainable solutions.

4. Results and Analysis

4.1 Preliminary Machine Learning – Models for Asphalt Concrete

The method of manually checking whether a pavement photo contains various pavement distresses is time-consuming and ineffective since it requires human staff to review each photo. To resolve this problem, the research team is developing a solution that utilizes AI's machine learning techniques. The goal is to develop a system that can accurately and efficiently identify photos with distresses, allowing for a more efficient and effective pavement management program.

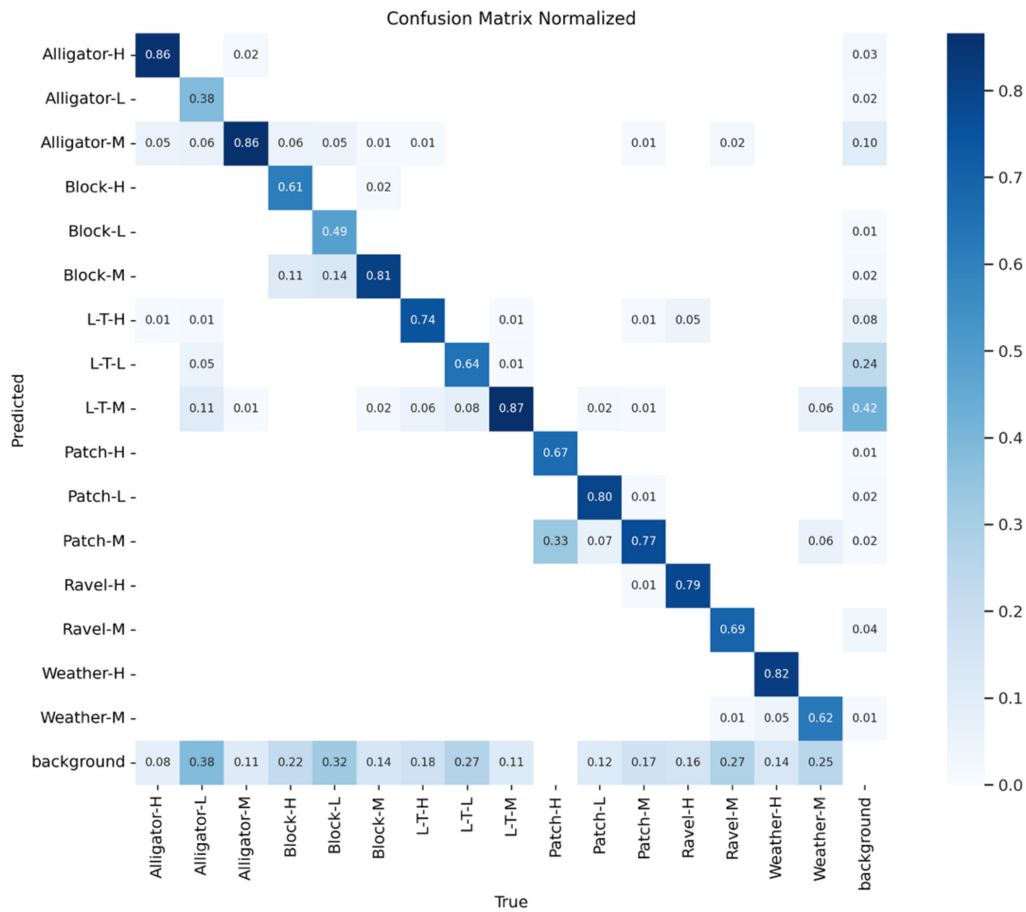
The evolution of machine learning algorithms in recent years has been remarkable, particularly in the field of image recognition and classification. Algorithms can detect intricate patterns and anomalies after being trained. By utilizing advanced machine learning algorithms, the research team has developed machine learning models to identify pavement distress on submitted videos and photos.

4.2.1 Classification Model

VGG16 supports 16 convolutional layers in the model, which is a convolutional neural network model proposed by A. Zisserman and K. Simonyan from the University of Oxford (Simonyan & Zisserman, 2015). The VGG16 model achieves almost 92.7% top five test accuracy in ImageNet, which is a dataset consisting of more than 14 million images belonging to nearly 1,000 classes. The images for this research were divided into a training group and a testing group.

The VGG16 classification model provided good results for classifying pavement distress photos. As shown in Table 1, 16 distresses types have been modeled. They include alligator-h (alligator cracking – high severity), alligator-l (alligator cracking – low severity), alligator-m (alligator cracking – medium severity), block-h (block cracking – high severity), block-l (block cracking – low severity), block-m (block cracking – medium severity), L-T-H (longitudinal/transverse cracking – high severity), L-T-L (longitudinal/transverse cracking – low severity), L-T-M (longitudinal/transverse cracking – medium severity), Patch-H (patching and utility cut – high severity), Patch-L (patching and utility cut – low severity), Patch-M (patching and utility cut – medium severity), Ravel-H (raveling – high severity), Ravel-M (raveling – medium severity), Weather-H (weathering – high severity), and Weather-M (weathering – medium severity). The confusion matrix shows that, for the most common cracking distresses, 86% of alligator-h and alligator-m photos were correctly identified; 81% of block-m cracking photos were correctly identified; and 87% of longitudinal and transverse-m cracking photos were correctly identified.

Table 1. Classification Model Results – Confusion Matrix



4.2.2 Distress Detection Model

YOLOv11, the latest advancement in the YOLO series developed by Ultralytics, represents one of the most cutting-edge model architectures for object detection. Building upon the success of YOLOv8, it introduces enhanced neural network optimizations, further improving both speed and accuracy. This allows for even faster and more precise detection of objects in images. Since its inception, the YOLO family has seen continuous refinements, with YOLOv11 being the newest iteration as of 2025. Its applications span across classification, object detection, segmentation, pose estimation, and tracking (Ultralytics, 2025). For the task of detecting pavement distresses in submitted photos, the YOLOv11 model has been selected due to its superior performance. The dataset was split into three sets: 70% training, 20% validation, and 10% testing.

Table 2 shows the YOLO parameter results during the training process. An epoch represents one complete iteration over the entire training data. Multiple epochs allow the model to learn from the data gradually and refine its internal representations. In each epoch, the model computes predictions for each training sample, calculating the loss (error) between the predicted values and actual labels, and the optimizer of the model adjusts the model's parameters to minimize this loss. The number of epochs for training is an important parameter (hyperparameter). In machine learning, a hyperparameter is a parameter whose value controls the behavior of the learning algorithm and is set before the training, while a model parameter is learned during training. The practitioner sets up the epochs before the training begins. Too few epochs may result in underfitting, while too many epochs can lead to overfitting. To prevent overfitting, the research team has monitored the validation loss during the training. The number of epochs was set as 150. The precision in the table measures the ability of the model to identify true positives among all the predicted positive instances in the validation dataset. The recall assesses the model's capability to find all the true positives, asking the question: "Out of all the ground truth positive samples, how many did the model correctly detect?" The Recall of the distress identification is 0.7351, which is calculated as (True Positive)/(True Positive + False Negative); the Precision of the distress identification is 0.6992, which is calculated as (True Positive)/(True Positive + False Positive).

The mAP50 means Mean Average Precision at Intersection over Union (IoU) threshold 0.50. The AP is the area under the precision-recall curve for each class, and mAP is the mean of the AP values across all classes. The IoU 0.50 considers a detection as correct if the overlap between the predicted bounding box and the ground truth bounding box is at least 50%. The mAP50-90 extends the evaluation to a range of IoU thresholds. Instead of just considering IoU at 0.50, it computes AP values across a spectrum of IoU thresholds from 0.50 to 0.960. The final mAP50-90 is the average of these AP values. Higher mAP values indicate better object detection performance and are suitable for a broad assessment of model performance. The IoU is essential when precise object location is crucial.

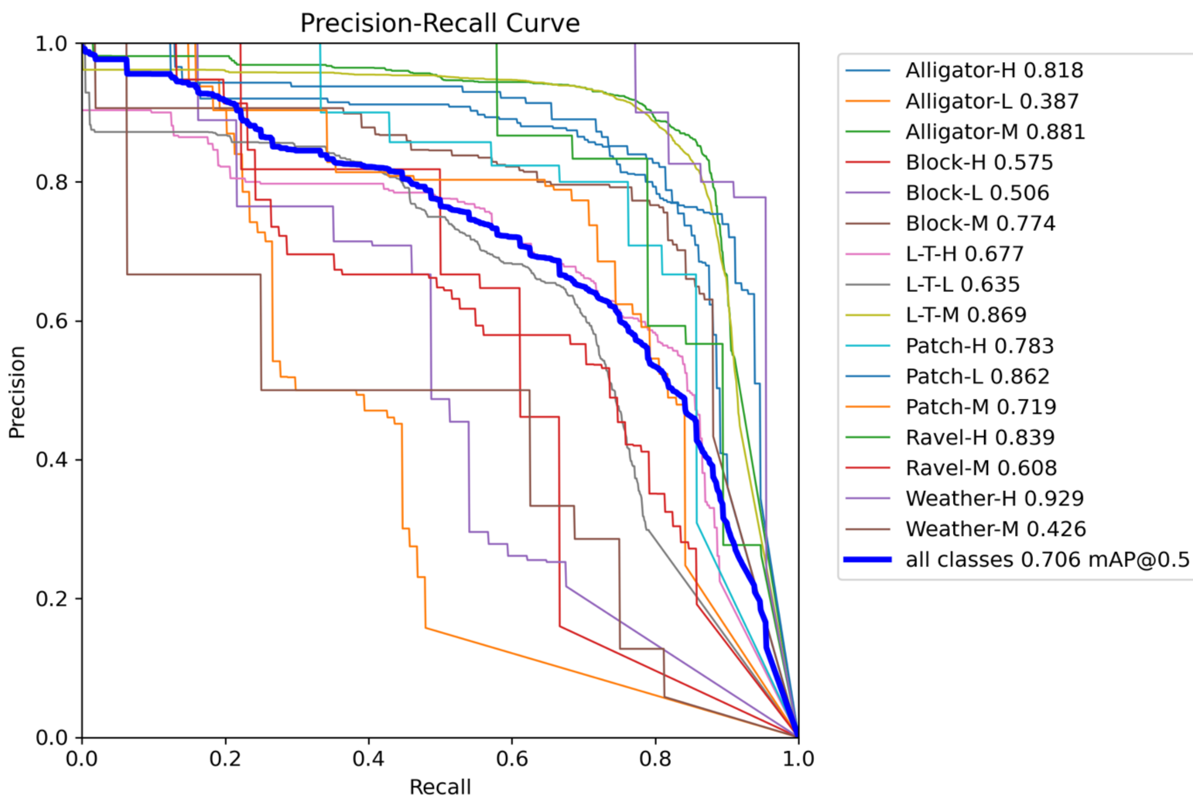
As shown in Table 2, as epochs increase, all metrics—including precision, recall, mAP50, and mAP50-90—also increase. In the end, these metrics level off or decrease with the increase of epochs; therefore, the training stops. At epoch 140, precision reaches the highest value. At epoch 125, recall reaches the highest value. At epoch 150, mAP50 and mAP50-90 reach the highest value. The training weights and results at epoch 150 are saved as the best parameters for the model.

Table 2. Results of ML Training Parameters

epoch	metrics/precision	metrics/recall	metrics/mAP50	metrics/mAP50-95
1	0.33155	0.24605	0.19738	0.14201
5	0.28799	0.33101	0.26442	0.18104
10	0.38279	0.48908	0.43084	0.33543
15	0.51247	0.5563	0.54349	0.43622
20	0.56516	0.59417	0.59281	0.50053
25	0.57896	0.62998	0.61263	0.52844
30	0.55987	0.67747	0.62713	0.54041
35	0.58317	0.67654	0.63447	0.55051
40	0.59068	0.68054	0.64001	0.55813
45	0.59527	0.69987	0.65047	0.57127
50	0.61019	0.69291	0.65586	0.58008
55	0.61422	0.70125	0.66412	0.59151
60	0.62225	0.70477	0.6716	0.60119
65	0.60581	0.72892	0.67343	0.60424
70	0.60134	0.73487	0.67656	0.60824
75	0.61079	0.72526	0.68029	0.61329
80	0.62345	0.72168	0.68443	0.61746
85	0.63769	0.71747	0.68786	0.62244
90	0.64236	0.71735	0.68953	0.62464
95	0.63468	0.73231	0.69193	0.62784
100	0.63232	0.73163	0.69262	0.63004
105	0.64568	0.7253	0.69483	0.63364
110	0.66057	0.71977	0.69797	0.6374
115	0.66948	0.7192	0.70051	0.64089
120	0.66048	0.7257	0.70289	0.64522
125	0.66488	0.7351	0.70415	0.64876
130	0.66153	0.72865	0.70213	0.64889
135	0.68237	0.70085	0.70302	0.65028
140	0.6992	0.68851	0.70104	0.65193
145	0.68465	0.71016	0.70708	0.65944
150	0.69039	0.70521	0.71073	0.66443

Figure 1 is the precision-recall curve of the object identification model. Generally, the higher the curve is in the upper right corner, the larger the area under the curve, indicating a higher Average Precision (AP) and better machine learning models. In this case, the AP for all distress types is 0.706 (70%), which means that the locations of most of the distresses can successfully be identified.

Figure 1. Precision-Recall Curve of ML Model



4.2 Sample Machine Learning Model Prediction Results

The research team has developed some preliminary models that can be used to identify cracking distresses in asphalt pavements. As an example, Figure 2 shows that five cracking types (alligator-h, alligator-m, alligator-l, L-T-M, L-T-L) and their locations are identified in the photo by the machine learning model. Figure 3 illustrates that alligator-m and L-T-L were identified even with the shade of trees on the road.

Figure 2. Example of Cracking Detection by the ML Model

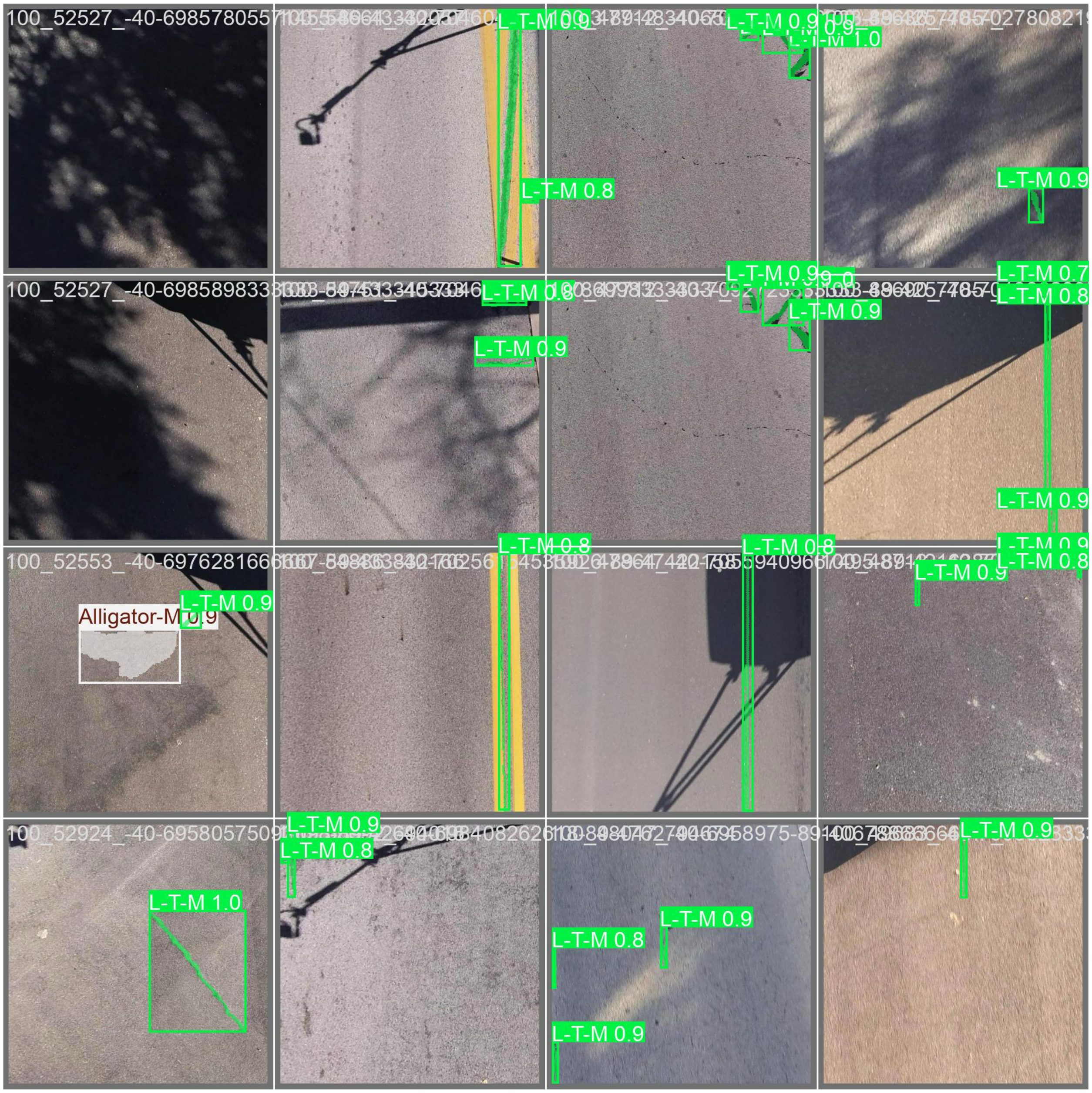
(a) Original Pavement Image (b) Alligator Cracking and L-T Cracking

Figure 3. Example of Cracking Detection by the ML Model in Shade

(a) Road Image with Shade (b) Road Image with Prediction Results

Figure 4 shows the asphalt pavement distress identification results on one batch of 16 photos. For most of the photos, the developed YOLO model can identify all photos that do not have any distresses. The model is also able to identify all photos that have distresses. However, not all ground truth distresses are identified. For example, a transverse cracking in the third photo in the top row is missed by the model. Therefore, there is room for improvement in the pothole detection model.

Figure 4. Batch Prediction of Distresses on 16 Photos



5. Conclusions and Recommendations

In summary, a prototype of the asphalt pavement cracking distress identification program has been developed, which includes customized machine learning models.

5.1 Conclusions

The following are conclusions from this study:

1. A comprehensive framework has been developed that utilizes machine learning techniques to automatically detect and classify cracking distresses in asphalt pavements, enabling more accurate, consistent, and efficient pavement condition assessments compared to traditional visual inspections.

2. Artificial Intelligence and Machine Learning enhance asphalt pavement inspection by improving the accuracy of detecting pavement distresses and increasing efficiency through faster, automated analysis compared to traditional manual methods.

3. Deep learning models have the capability to automatically detect and recognize a wide range of cracking distresses in asphalt pavement.

5.2 Recommendations

The following are the recommendations from this study:

1. Using machine learning models, it is possible to identify a broad range of pavement distresses beyond cracking, such as potholes, rutting, raveling, and surface wear, thereby enabling more comprehensive pavement condition evaluation.

2. Automated systems support data-driven maintenance by continuously collecting and analyzing pavement condition data, enabling transportation agencies to make timely, informed decisions that optimize repair strategies, reduce costs, and extend pavement lifespan.

3. It is possible to incorporate distress identification models into pavement management systems to automate the evaluation of roadway conditions; Therefore, this could streamline decision-making, and support the development of more effective, data-driven maintenance and rehabilitation strategies.

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