Ai Car With Real-Time Detection of Damaged Road and Lane Detection

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***Abstract*— The field of vehicles is moving really fast and this means we need to create smart systems that can make sure vehicles are safe on the road. Things like potholes and cracks in the road well as bad lane markings are the main reasons for accidents and bad driving Normally people check the road by looking at it themselves with tools. This way is slow expensive. Cannot give us answers right away. To make this better we are suggesting a system that uses Artificial Intelligence to find road damage in time so autonomous vehicles can be safer and more efficient. This system uses a camera on the vehicle and computer vision to look at the road. The deep learning model uses the You Look Once framework to find out what is on the road like potholes and cracks and where the lane markings are so the vehicle can stay in its lane. It does this by looking at videos one frame at a time which means it can detect things fast even when it is dark or the lane lines are hard to see. Our tests show that this system is very good at finding road damage with confidence levels above 0.88 and it is also very good at finding lane markings with accuracy, between 92% and 95%. Our Artificial Intelligence system shows that we can use Artificial Intelligence, computer vision and deep learning to make road inspection which means we can take better care of our roads spend less money on maintenance and create safer and smarter transportation systems. The autonomous vehicles and road damage detection and lane detection are all parts of this. We use computer vision and deep learning and the YOLO Object Detection to make this work. The Artificial Intelligence and autonomous vehicles and road damage detection are all connected.**

***Index Terms*— Artificial Intelligence, Autonomous Vehicles, Road Damage Detection, Lane Detection, Computer Vision, Deep Learning, YOLO Object Detection, Real-Time Monitoring, Smart Transportation Systems.**

I. INTRODUCTION

The development of intelligent transportation systems has received important contributions from Artificial Intelligence (AI) and machine learning and computer vision technologies according to research from source [17] and source [20]. Modern vehicles now use smart systems that help drivers monitor road conditions and stay in their lanes and protect themselves from potential dangers. The Advanced Driver Assistance Systems (ADAS) and autonomous vehicles use these technologies to enhance road safety while achieving better driving performance according to source [8]. The vehicle uses cameras and sensors to monitor its surroundings in real time which enables it to detect objects and road signs and pedestrians and lane markings according to research from source [15]. Drivers in developing countries face their biggest challenge when they drive on poorly maintained roads. Heavy traffic and weather conditions plus insufficient maintenance all contribute to the development of potholes and cracks and uneven road surfaces. The damaged roads create dangerous conditions which lead to accidents while causing vehicle damage and traffic delays and making driving less comfortable according to research from source [3] and source [6]. Safe driving requires drivers to maintain correct lane discipline throughout their time on the road. Lane detection systems help drivers stay within their designated lanes and prevent lane departure accidents according to sources [4] and [9] and [10]. Road safety improves when road damage detection and lane detection systems merge into a unified intelligent system. Many traffic accidents involve undetected damage to roads such as potholes, cracks, or irregular surfaces, meaning that drivers may not notice these defects before hitting them, especially at high speed or during low lighting conditions according to research from source [3] and source [6].

II. RELATED WORK

Road Safety Is a Global Priority for All People. Road Damage Causes Increased Vehicle Repair Costs and Road Traffic Accidents and Road Damage Will Result in Increased Vehicle Repair Cost and Accident. Road Infrastructure Is Not Regularly Checked in Many Parts of The World, And Some Regions Take a Long Time for Road Repairs.

Real-Time Detection of Road Damage Would Provide Drivers with Valuable Information About When They Should Slow Down or Change Lanes Safely [3], [6]. Accurate Lane Detection Would Allow Vehicles to Stay Within the Lane, Thus Reducing the Chance of An Accidental Lane Departure and An Accident [4], [9], [10]. A Road Monitoring System That Can Detect Both Lane Position and Road Damage Can Significantly Improve Driving Safety While Providing a Basis for The Development of Intelligent and Autonomous Vehicles [17], [20].

Currently, Road Monitoring Systems Use Manual Survey Methods, Summative Inspection Vehicles, And Driver Reports to Monitor the Condition of Roads [15]. These Methods Are Relatively Expensive, Time Consuming, And Fail to Provide Real-Time Information About Road Conditions. Some Recent Vehicles Have Lane Detection Technologies Built into Them; However, These Systems Primarily Focus on Lane Keeping Rather Than Detecting Road Surface Damage [4], [9]. Many Road Surface Damage Detection Methods Exist but Do Not Integrate with Lane Detection Methodologies [3]. Finally, The Use of Computer Vision to Detect Road Lane and Road Damage Often Does Not Work When the Conditions Are Poor Such as When There Is Little to No Light, Shadowed Areas, Or Faded Road Markers.

Artificial Intelligence can be used to enhance Intelligent Transportation Systems as it allows for the development of vehicle systems that can detect road damage and lane markings in real-time with the help of Computer Vision and Deep Learning [8],[15]. By using a front-facing camera mounted on the vehicle, the system takes images of the road continuously, and using Machine Learning, provides a real-time analysis of each frame taken by the camera to detect potholes, cracks and other road surface irregularities [3],[6]. Lane Detection Techniques are able to determine the proper lane positioning on the road, and to assist the vehicle in maintaining that lane position [4],[10]. When either damaged lane markings have been detected, or the vehicle is no longer within the proper lane position, the system will alert the driver and assist in returning the vehicle to the correct lane position [11],[13]. The result of these systems is improved safety for drivers, and also provides the authorities an accurate set of information regarding the condition of the road.

Artificial Intelligence provides very significant improvements to Intelligent Transportation Systems because it allows for the quick, accurate analysis of large amounts of visual data [17]. Deep Learning Algorithms are able to analyze images of roads and detect patterns within those images that may not be apparent to an average human driver [7]. These Models can detect small cracks or partially damaged lane markings and warn drivers accordingly [15]. Another essential component of Intelligent Driving Systems is Real-time Image Processing. The cameras, which are located in vehicles, are constantly taking images of the road. Deep learning techniques have drastically enhanced the precision of roadway identification systems. Convolutional neural networks (CNNs) can automatically extract visual attributes from roadway pictures and spot many types of roadway problems including potholes, cracks and/or uneven surfaces [3]. Object recognition algorithms such as YOLO are able to quickly and precisely distinguish roadway dangers and make them appropriate for use in dynamic time-critical applications. Such applications include those associated with driver assistance technologies and with autonomous driving systems [7][8]. Integrating the identification of roadway damage into systems that identify lanes delivers a far greater comprehensive solution to the general safety of roadways [17][20].

III. LITERATURE SURVEY

S.no	Author	Title	Method Used	Limitattions
1.	Kalapraveen Bagadi, Naveen Kumar Vaegae, Visalakshi Annepu, Shafiq Ahmad, Khaled Rabie, Thokozani Shongwe.	Advanced Self-Driving Vehicle Model for Complex Road Navigation Using Integrated Image Processing and Sensor Fusion.	Image Processing, Sensor Fusion, EfficientDet-D0, HaarCascade, Camera + Ultrasonic sensors, Arduino, RaspberryPi, Decision-making algorithm.	Tested in artificial environment only, limited real-road testing, moderate accuracy, depends on sensor quality, hardware complexity.
2.	Rahman Shafique, Furqan Rustam, Sheriff Murtala, Anca Delia Jurcut, Gyu Sang Choi	Advancing Autonomous Vehicle Safety: Machine Learning to Predict Sensor-Related Accident Severity	Natural Language Processing,Machine Learning, MDST Data Balancing, Recursive Feature Selection, Ensemble Model	Small dataset (334 samples), depends on accident reports, limited real-world data, imbalance problem, may not generalize to all AV systems
3.	Alessio Gagliardi, V. Staderini, S. Saponara	An Embedded System for Acoustic Data Processing and AI-Based Real-Time Classification for Road Surface Analysis	Acoustic signal processing, CNN, Mel Spectrogram, Embedded system, IoT, Bluetooth Low Energy	Works only with acoustic data, limited road types, affected by noise, requires sensor installation, tested in limited area
4.	Luís Augusto Silva, Valderi Reis Quietinho Leithardt, Vivian Félix López Batista, Juan Francisco de Paz Santana, Gabriel Villarrubia González	Automated Road Damage Detection Using UAV Images and Deep Learning Techniques	UAV imaging, Deep Learning, YOLOv4, YOLOv5, YOLOv7, Transformer Prediction Head	Requires UAV, high cost, depends on image quality, weather conditions affect results, moderate accuracy
5.	Teena Sharma, Issouf Fofana, Abdellah Chehri, Shubham Jadhav, Siddhartha Khare, Deeksha Arya, Benoit Debaque, Nicolas Duclos-Hindie	Deep Learning-Based Object Detection and Classification for Autonomous Vehicles in Different Weather Scenarios of Quebec, Canada	Deep Learning, YOLOv8, CNN, Custom Dataset (CVD), Image Annotation, Object Detection	Limited dataset size, weather-specific data, moderate accuracy, high training cost, requires high computing power
6.	Rashed Al Amin, Mehrab Hasan, Veit Wiese, Roman Obermaisser	FPGA-Based Real-Time Object Detection and Classification System Using YOLO for Edge Computing	YOLOv3-Tiny, FPGA, Edge Computing, Deep Learning, Vitis AI, Traffic Light Detection	Works only for limited objects, requires FPGA hardware, costly setup, trained on small dataset, limited FPS
7.	Mohd Ibrahim Shapiai, Noor Jannah Zakaria, Rasli Abd Ghani,	Lane Detection in Autonomous	Systematic Literature Review, Deep Learning, Machine Learning,	Review paper only, no implementation, depends on existing datasets,

	Mohd Najib Mohd Yassin, Mohd Zamri Ibrahim, Nurbaiti Wahid	Vehicles: A Systematic Review	Geometric Modeling, ADAS, CNN, Attention Mechanism	performance varies in extreme weather, high computation for deep learning
8.	Amel Ali Alhussan, Doaa Sami Khafaga, El-Sayed M. El-Kenawy, Abdelhameed Ibrahim, Marwa Metwally Eid, Abdelaziz A. Abdelhamid	Pothole and Plain Road Classification Using Adaptive Mutation Dipper Throated Optimization and Transfer Learning for Self-Driving Cars	AMDTO Optimization, Random Forest, Feature Selection, Transfer Learning, SMOTE, Machine Learning, Dataset Augmentation	Complex algorithm, high computation, requires training data, real-time performance not tested, implementation difficult
9.	Jing Huang, Lingyun Zhu, Pallab K. Choudhury, Song Yin	Real-Time Road Curb and Lane Detection for Autonomous Driving Using LiDAR Point Clouds	LiDAR Point Cloud Processing, Constrained RANSAC, Density-based Curb Detection, Adaptive Threshold, Lane Detection Algorithm	Requires LiDAR sensor, costly hardware, sensitive to noise, high computation, performance depends on point cloud quality
10.	Samia Sultana, Muhammad Rafiqul Islam, Boshir Ahmed, Manoranjan Paul, Shamim Ahmad	Vision-Based Robust Lane Detection and Tracking in Challenging Conditions	Canny Edge Detection, CITR Threshold, Hough Transform, Geometric Constraints (AGC, LGC), Lane Tracking Algorithm	Sensitive to lighting changes, camera quality required, fails in extreme weather, needs preprocessing, high computation for real-time

IV. DESCRIPTION

Paper 1: This research presents a self-driving vehicle system that operates in complex road environments. The system achieves precise environmental understanding through image processing combined with sensor fusion technology. The system uses EfficientDet-D0 and Haar Cascade to identify both traffic signs and obstacles. The system creates a 2D navigation map through its camera and ultrasonic sensor components. The system demonstrates effective performance during testing but requires advanced hardware and actual road testing to validate its capabilities.

Paper 2: The study uses accident severity predictions to enhance safety measures in self-driving vehicles. The research analyzes accident reports dataset through NLP methods. The combination of feature selection and data balancing techniques results in better model performance. The ensemble machine learning system achieved approximately 92% accuracy. The results depend on two factors which are dataset quality and dataset size limitations.

Paper 3: The research uses acoustic signals to study different types of road surfaces. The system transforms wheel-road sound into Mel spectrogram images. The CNN model classifies road quality into four different categories. The embedded board system produces real-time output during operation. The system performance depends on two factors which are sound quality and sensor position.

Paper 4: The research uses UAV drone images to identify and analyze road damage. The research compares three deep learning models which are YOLOv4, YOLOv5, and YOLOv7. The system achieves highest accuracy through YOLOv7 which detects both cracks and potholes. The system enables automated road inspection processes which decrease manual inspection requirements. The use of drones increases operational costs and their functionality becomes dependent on weather conditions.

Paper 5: The research investigates how weather conditions affect the ability to detect objects. The researchers constructed a new dataset which contains snow, rain, night, and sunny images. The YOLOv8 model identifies 11 different object classes through its detection capabilities. The model maintains strong performance throughout all weather conditions. The model requires extensive computational resources and its training process is restricted by the available dataset size.

Paper 6: The research develops a traffic light detection system that operates in real-time through the use of FPGA technology and deep learning methods. The system uses YOLOv3-Tiny model for rapid object detection capabilities. The system uses FPGA hardware for its operations.

Research Papers

Paper 1: Advanced Self-Driving Vehicle Model for Complex Road Navigation Using Integrated Image Processing and Sensor Fusion

This paper proposes a self-driving vehicle model for complex road environments. Image processing and sensor fusion are used for accurate perception. EfficientDet-D0 and Haar Cascade detect traffic signs and obstacles.

Link: https://ieeexplore.ieee.org/document/10737305

Paper 2: Advancing Autonomous Vehicle Safety: Machine Learning to Predict Sensor-Related Accident Severity

This paper predicts accident severity to improve autonomous vehicle safety. Accident reports dataset is analyzed using NLP techniques. Feature selection and data balancing improve model performance.

Link: https://ieeexplore.ieee.org/document/10439194

Paper 3: An Embedded System for Acoustic Data Processing and AI-Based Real-Time

Classification for Road surface Analysis

This paper analyzes road surface type using acoustic signals. Wheel-road sound is converted into Mel spectrogram images. A CNN model classifies road quality into four categories.

Link: https://ieeexplore.ieee.org/document/9795266

Paper 4: Automated Road Damage Detection Using UAV Images and Deep Learning Techniques

This paper detects road damage using UAV drone images. Deep learning models YOLOv4, YOLOv5, and YOLOv7 are compared. YOLOv7 gives best accuracy for crack and pothole detection.

Link: https://ieeexplore.ieee.org/document/10155434

Paper 5: Deep Learning-Based Object Detection and Classification for Autonomous Vehicles in Different Weather Scenarios of Quebec, Canada

This paper studies object detection in different weather conditions. A new dataset with snow, rain, night, and sunny images is created. YOLOv8 model is used to detect 11 object classes.

Link: https://ieeexplore.ieee.org/document/10399478

Paper 6: FPGA-Based Real-Time Object Detection and Classification System Using YOLO for Edge Computing

This paper proposes a real-time traffic light detection system using FPGA and deep learning. YOLOv3-Tiny model is used for fast object detection. FPGA hardware is used for edge computing and high-speed processing.

Link: https://ieeexplore.ieee.org/document/10537163

Paper 7: Lane Detection in Autonomous Vehicles: A Systematic Review

This paper reviews different lane detection techniques for autonomous vehicles. More than 100 research papers are analyzed and compared. Both traditional image processing and deep learning methods are studied.

Link: https://ieeexplore.ieee.org/document/10006813

Paper 8: Pothole and Plain Road Classification Using Adaptive Mutation Dipper Throated Optimization and Transfer Learning for Self-Driving Cars.

This paper proposes a pothole and plain road classification system. Road images are processed using feature selection optimization. Random Forest classifier is used for classification.

Link: https://ieeexplore.ieee.org/document/9850988

Paper 9: Real-Time Road Curb and Lane Detection for Autonomous Driving Using LiDAR Point Clouds

This paper presents lane and curb detection using LiDAR point clouds. RANSAC algorithm filters background points. Point density method detects curb and road area. Adaptive threshold detects lane markings in real time.

Link: https://ieeexplore.ieee.org/document/9576699

Paper 10: Vision-Based Robust Lane Detection and Tracking in Challenging Conditions
This paper proposes a vision-based lane detection and tracking method. Canny edge detection and Hough transform are used. Geometric constraints verify correct lane lines. Tracking method predicts lane position in next frame.
Link: https://ieeexplore.ieee.org/document/10172163

V. PROPOSED METHODOLOGY

The deep learning model for road damage detection uses Convolutional Neural Networks (CNN) to assess road surfaces and detect various types of defects which include potholes and cracks as well as uneven surfaces [3][6]. Real-time road damage identification and localization is achieved through the application of object detection algorithms which include YOLO [7][8]. The system uses bounding boxes to show identified damages while it displays lane boundaries on the original video frame. The system produces alerts through combined result analysis which detects road damage and lane deviation to enhance driving safety and decision-making process [11][20].
The proposed system's web interface was created using HTML and CSS alongside JavaScript and the Flask framework. The frontend includes several pages such as Home, Login, Signup, Detect, Features, About, and Contact. The pages connect to the backend server which handles user input while showing current detection outcomes. Web-based platforms are widely used for deploying intelligent vehicle monitoring systems because they allow easy integration between AI models and user interfaces [17].

5.1 Home Page

The Home page serves as the main entry point of the system. The system introduces its AI Car system through this page which detects road damage and lane markings in real time. The page provides navigation links for Login Signup Detect Features About and Contact. The system shows safety benefits of AI-based road monitoring systems which enable autonomous driving through its visual and descriptive content [17] [20].

5.2 Login Page

The Login page allows registered users to securely access the system. Users enter a valid username and password, which are verified through the backend server. Authentication mechanisms protect intelligent transportation systems and monitoring platforms through their function of maintaining system access security [16].

5.3 Signup Page

The Signup page allows new users to register by providing details such as username, email, and password. The backend server stores the entered information into an SQLite database. Secure user authentication helps maintain controlled access to AI-based monitoring systems [16].

5.4 Detect Page

The Detect page serves as the main operational interface for the system. The system supports three detection methods through its user interface which enables users to upload images and videos and stream from their webcams. The backend server processes uploaded media and webcam streams using YOLO-based object detection and computer vision algorithms to analyze video frames [7] [8]. The system generates multiple results which include pothole detection and road damage detection and lane detection and bounding boxes and warning alerts [3] [6].

5.5 Features Page

The Features page provides an overview of the system's primary functionalities. The system provides five different capabilities which include real-time road damage detection and lane detection through computer vision and YOLO-based object detection and live webcam detection and video analysis. AI-powered monitoring systems function as essential elements within contemporary intelligent transportation systems [17], [20].

5.6 About Page

The About page provides detailed information about the project objectives and development technologies. The system uses road damage detection and lane detection features to enhance the safety of autonomous driving technology [15], [17].

5.7 Contact Page

The Contact page enables users to communicate with system administrators or developers. The system allows users to send feedback and report problems and suggest better ways to improve the system. Feedback systems are important for improving intelligent transportation technologies based on actual system operation and performance measurement in real-world situations [17].

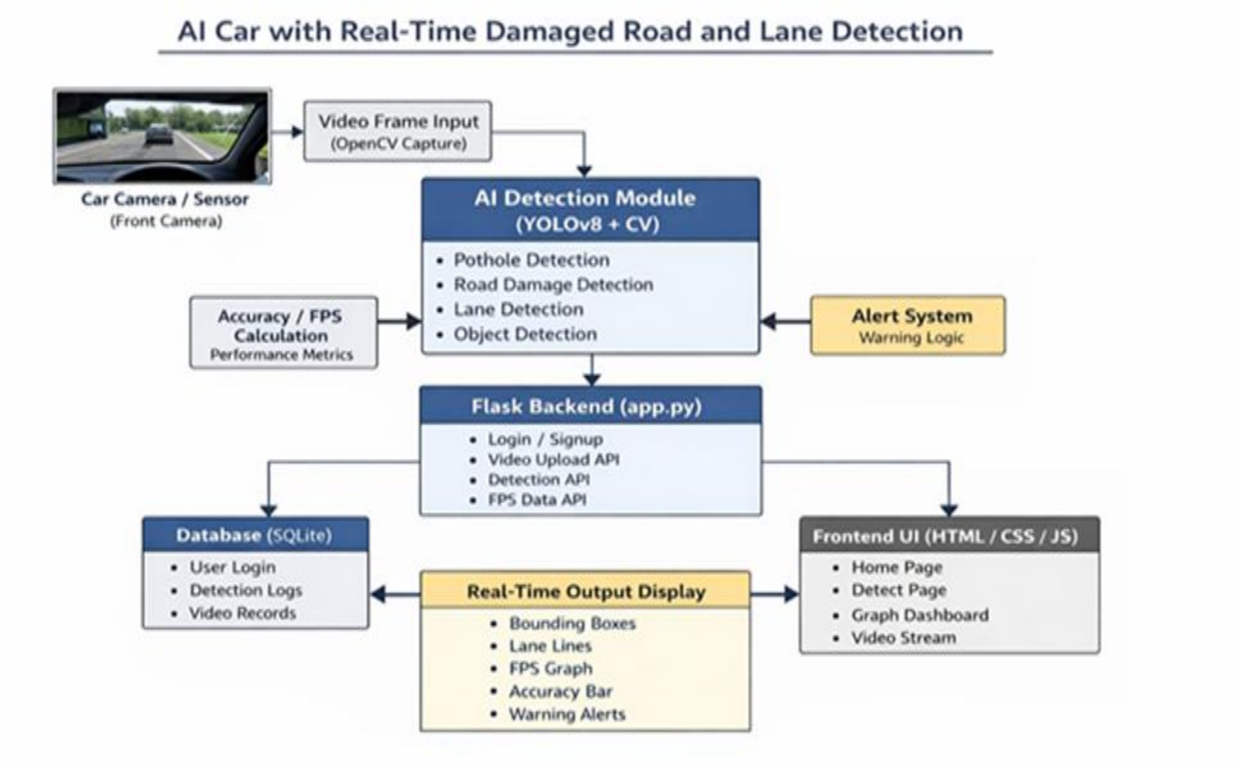


Figure 1: System Architecture

VI. ALGORITHM USED

In the proposed system, various algorithms and techniques in computer vision are used to detect damaged roads and lane markings in real time. The various algorithms used in the proposed system include Convolutional Neural Network, YOLOv8, and OpenCV. All these algorithms together process the video frames, detect road damage, and find the lane boundaries.

Convolutional Neural Network (CNN)

A Convolutional Neural Network is an image classification algorithm that uses deep learning techniques. This algorithm is used in image classification, object detection, and image segmentation. It automatically learns the important features in an image, like edges, texture, and shape. This algorithm is used in the proposed system to detect the damages in the roads. It is used to process the road image and detect the damages like potholes and cracks. After training the network with various road images, it can easily classify between normal roads and damaged roads.

YOLOv8 (You Only Look Once Version 8)

YOLOv8 is a state-of-the-art object detection model that is effective for object detection in real-time. Unlike other object detection models that require the entire network to pass through the input image several times, YOLOv8 detects objects in a single pass. This model is effective for detecting objects in real-time. In this project, the YOLOv8 model is applied to the detection of road damages such as potholes and cracks in the video frames. This model is effective for the detection task due to its high detection accuracy and speed.

OpenCV (Open-Source Computer Vision Library)

OpenCV is a computer vision library that is primarily used for computer vision applications. In this project, OpenCV is applied for the preprocessing of the video frames captured from the video. OpenCV is effective for enhancing the quality of the video frames. It detects lane lines using various techniques such as Canny Edge Detection and Hough Transform. This enables the detection of lane lines on the road clearly.

Integration of Algorithms

The proposed system uses a combination of CNN, YOLOv8, and OpenCV algorithms. The algorithms used in the system include OpenCV for video frame preprocessing and lane detection. The CNN and YOLOv8 algorithms are used for accurate road damage detection. The algorithms used in the system allow it to process video frames in real time, detect lanes, and detect road damage. The use of these algorithms in the proposed system makes it efficient in terms of accuracy.

Flow chart

The proposed system's workflow begins with the collection of the dataset, wherein road images are collected from online sources and image capture is done at the site. The images are taken under various road conditions such as potholes, cracks, and lane markings. The collected dataset is then passed through the preprocessing stage. The preprocessing stage includes normalization, data augmentation, and annotation. Normalization normalizes the collected dataset, while augmentation increases the diversity of the dataset. The dataset is then annotated with various features such as road damages and lane boundaries. The dataset is then split into the training and testing sets.

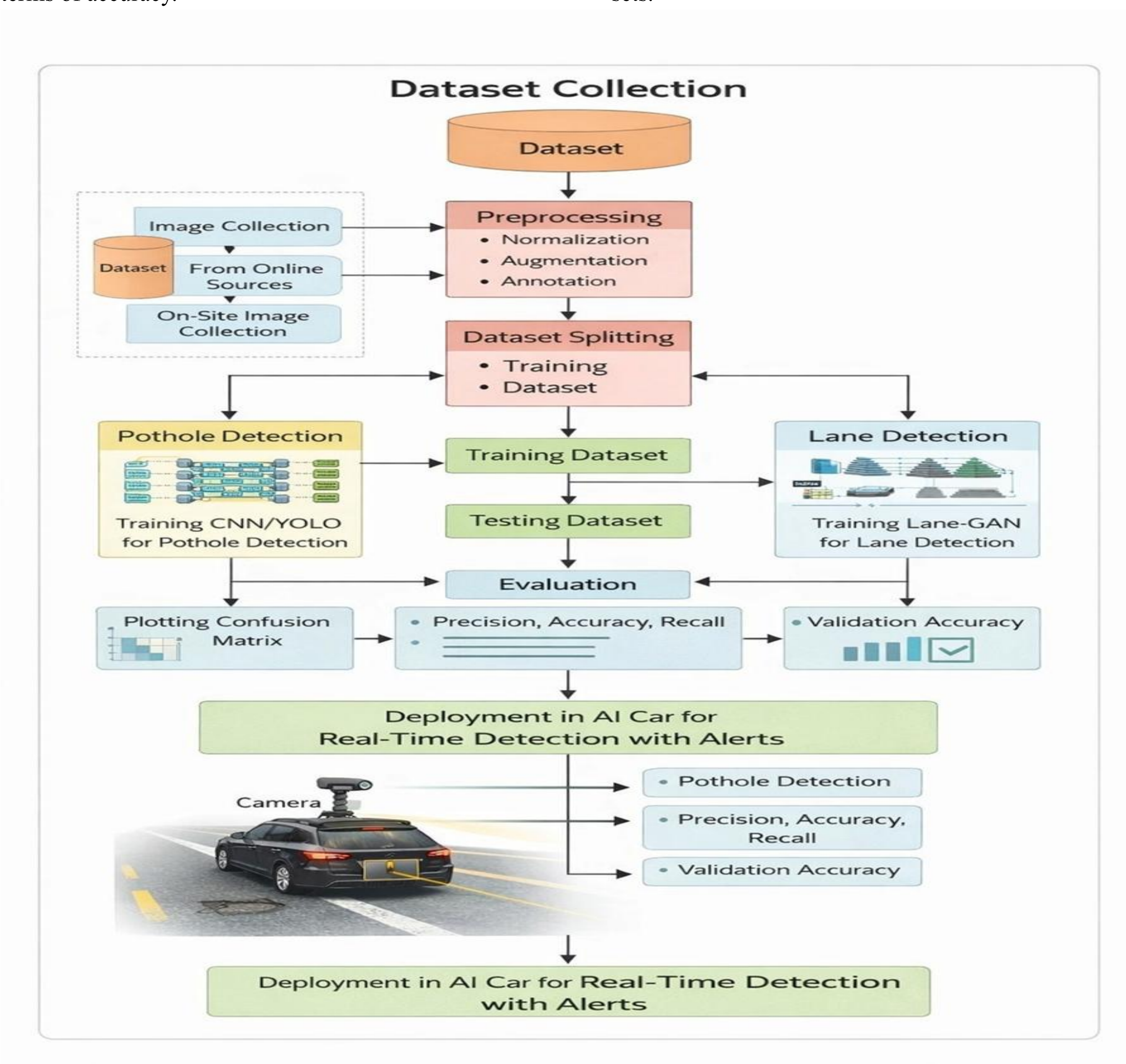


Figure 2: Flow Chart

VII. BLOCK DIAGRAM

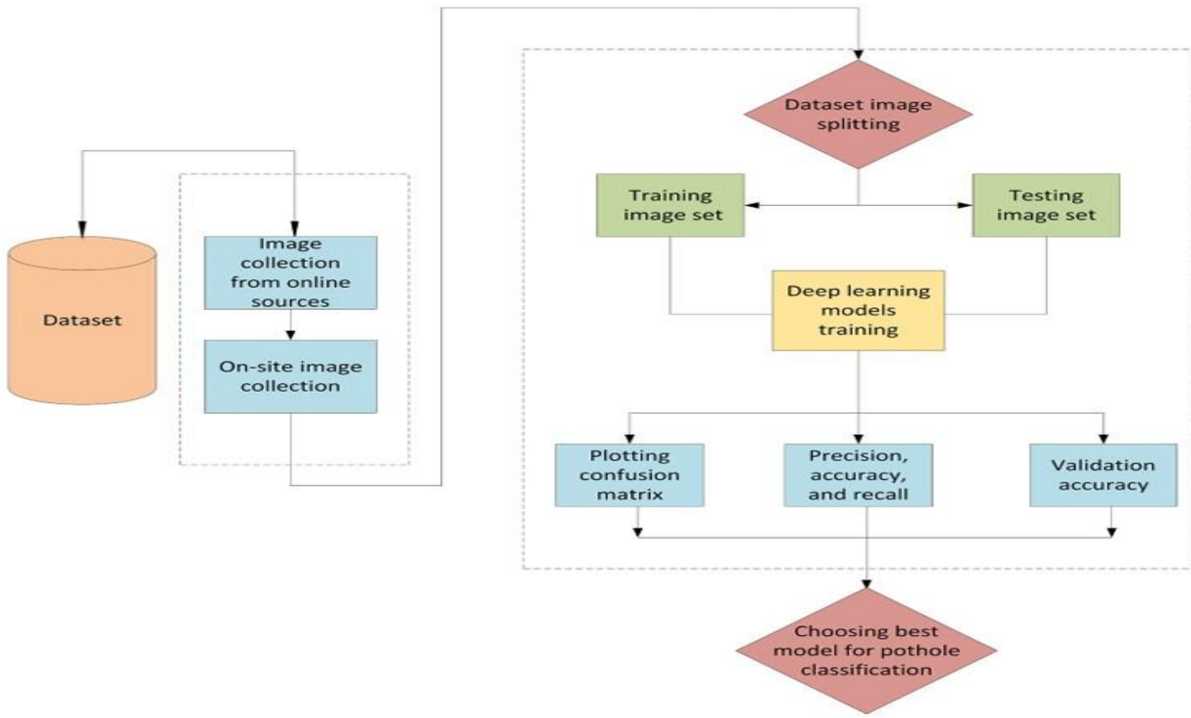


Figure 3: Block Diagram

The block diagram shows the workflow of the pothole and lane detection using deep learning techniques. The workflow of the pothole and lane detection using deep learning techniques involves the following steps: first, the collection of the dataset, which involves the collection of road images from various sources such as online sources and image acquisition. The images collected form the major dataset. After collecting the images, the images are arranged and prepared for the next step.

In the training of the deep learning model, the system learns significant features related to potholes and road surface conditions. After the training of the model, the performance of the model is checked using various metrics such as precision, accuracy, and recall. Moreover, the classification of the model is performed using the confusion matrix and the validation accuracy of the model. Based on the results of the model, the best model is selected for the classification of potholes.

Step-by-Step Working (Input – Processing – Output)

The proposed system for the detection of damaged roads in real-time and the detection of lanes involves a structured architecture that transforms the video input into a significant output using computer vision and deep learning techniques such as CNN, YOLOv8, and OpenCV. The entire process can be divided into three stages: Input, Processing, and Output.

Input

The first step in this system is the input step. In this step, the vehicle is equipped with a camera that takes video of the road while the vehicle is in motion. The camera takes video of the road environment, which includes lane markings, road surfaces, other vehicles, and other defects such as potholes and cracks. The video is then converted into individual image frames.

Processing

The second stage is the processing stage, where the processed image frames are analyzed using various algorithms. Firstly, the image frames are preprocessed using OpenCV. At this stage, the input frame is converted to grayscale to simplify the image. The grayscale conversion makes it easy to process the image. At this stage, noise reduction techniques such as Gaussian blur are used to remove unwanted noise from the images. The techniques improve the quality of the images.

After preprocessing the images, the system extracts the features of the images. The edges of the images are detected using OpenCV techniques. The edges of the images contain important features that can be used to detect the lane markings on the road. The Region of Interest (ROI) of the images is set to include only the road area where the lane lines can be found. The Hough Line Transform method is used to detect straight lines on the road. At the same time, the system can detect road damage using deep learning algorithms. The preprocessed images are passed to the YOLOv8 object detection algorithm. The algorithm analyzes the images and detects damaged road areas such as potholes and cracks. The YOLOv8 object detection algorithm

Output

The final stage is the output stage. In this stage, the processed frame is displayed to the user with visual indicators. The road image shows detected lane lines which the system uses to display the correct driving path while it uses bounding boxes to mark damaged road areas which include potholes and cracks. The system produces an alert or warning message when it identifes a hazardous road condition. The system shows output in real time which enables the driver and autonomous system to detect hazards and respond with appropriate measures.

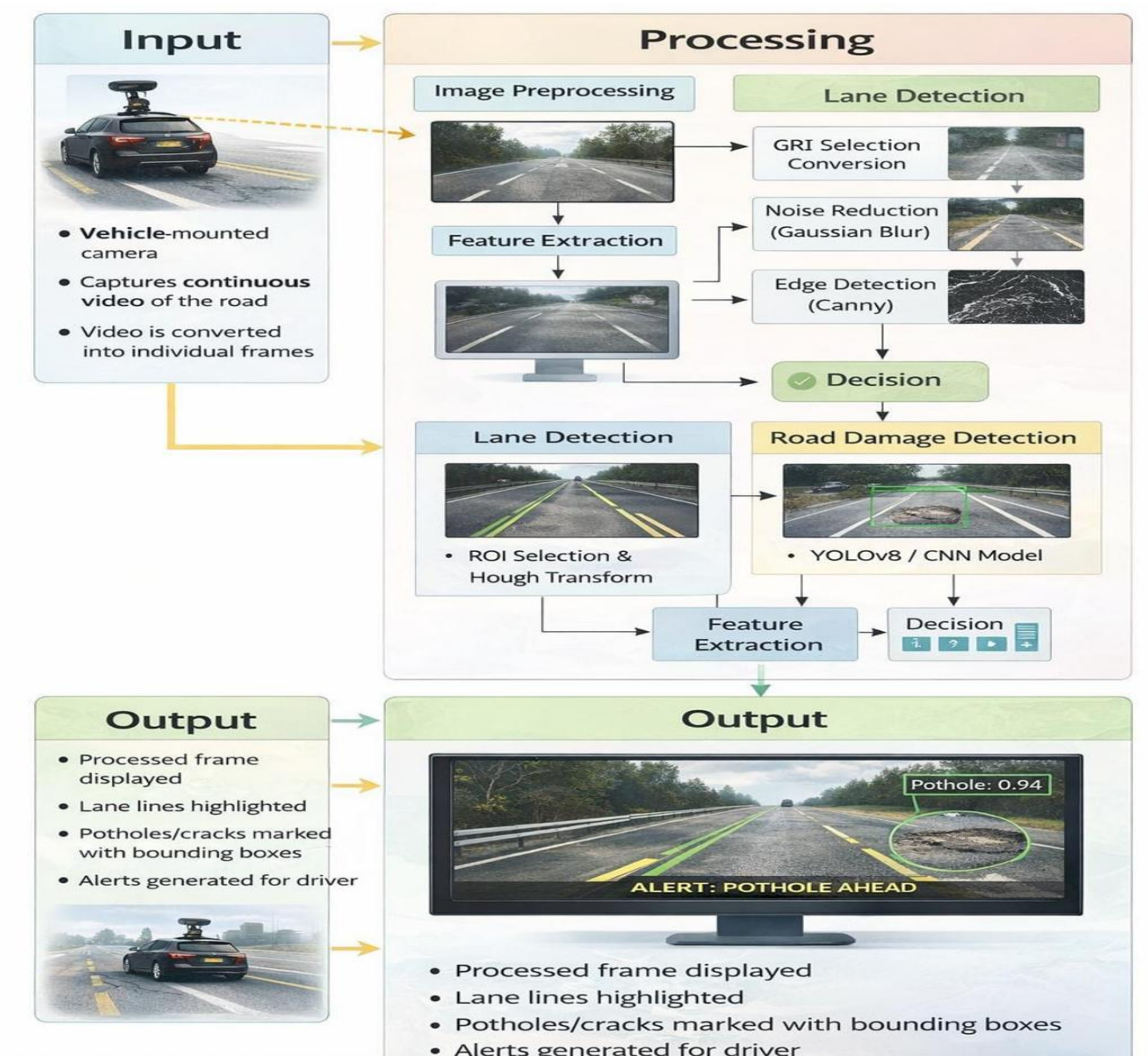


Figure 4: Step-by-Step Working Process

Implementation

Programming Language:

- Python serves as the main programming language which developers use to create the system.
- OpenCV provides users with tools to process images and manage video streams in real time.
- The system allows users to connect hardware components which include cameras and sensors.
- The system provides users with tools that enable them to create AI models quickly and deploy those models without delay.

Libraries Used:

- NumPy enables users to perform numerical calculations and execute matrix operations.
- Pandas enables users to prepare data for analysis while managing organized data formats.
- Matplotlib and Scikit-learn provide tools for displaying detection results while assessing model performance through various evaluation methods.
- YOLO (v5/v8) provides capability for detecting objects in real time.
- Streamlit and Flask provide an output display system for users to view results.

Tools Used:

- OpenCV enables users to perform image preprocessing tasks and detect edges and identify lanes on roads.
- YOLOv8 provides users with the ability to detect road damage in real time which includes potholes and cracks.
- The system uses CNN (Convolutional Neural Network) to extract visual characteristics from road images.
- NumPy provides users with tools to perform numerical calculations and manage image data using image arrays.
- Matplotlib enables users to create visual representations of their findings through graph displays and confusion matrix presentations.

Hardware Requirements

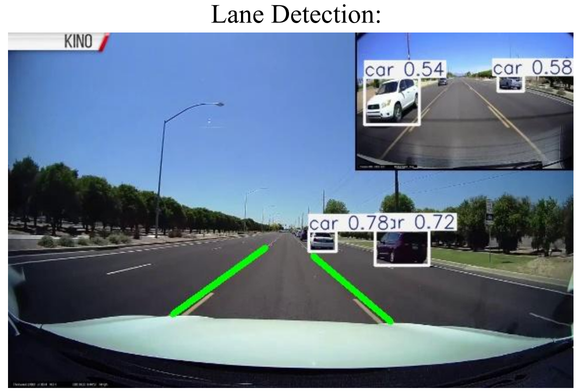
- Users need a computer that has an Intel Core i5 processor or a more advanced processor to run the model.
- Users require at least 8 GB RAM to process images and conduct model training.
- Users need to have 256 GB of storage space to store their datasets and models and their results.
- The system requires a vehicle-mounted high-resolution camera which will record video footage of the road.

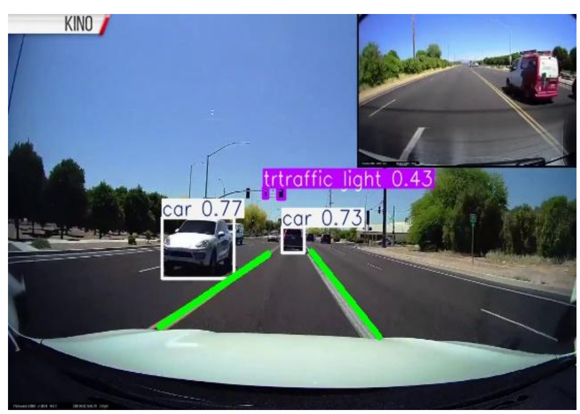
Software Requirements

- The system requires Python software version 3.8 or a later version for its implementation.
- OpenCV library provides users with image processing capabilities and tools for computer vision applications.
- Ultralytics YOLOv8 framework provides users with tools for detecting objects in their environment.
- The system requires TensorFlow or PyTorch software to train its deep learning models.
- Developers need to use VS Code and other development environments to write and verify their code.

VIII. RESULTS

Lane Detection:





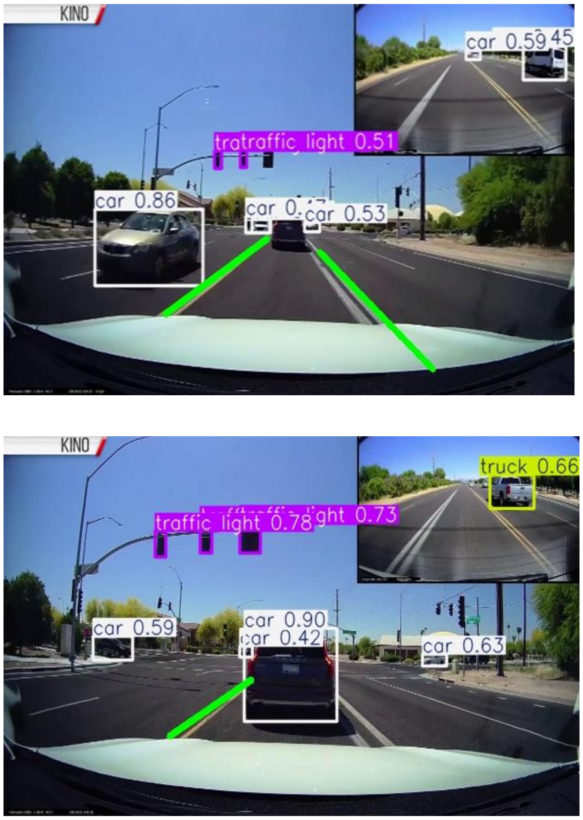


Figure 5: Outputs of Lane Detection

Road Damage Detection:

Figure 6: Outputs of Road Damage

The experimental results show the effectiveness of the proposed system in performing lane detection and road damage detection using deep learning techniques. The proposed system works by processing road video frames, detecting important features of the road, and ensuring driving safety.

In the lane detection part of the proposed system, the algorithm is used to detect the left and right lane boundaries in the given road images. The algorithm uses image processing techniques, edge detection, and region of interest detection to highlight the lane markings in the given road images. The experimental results show that the proposed model is effective in detecting lane positions in different road images. The model is also effective in detecting lane positions even when there are moving cars in the road. The lane detection part of the proposed model is useful in ensuring proper lane guidance in intelligent transportation systems.

In the road damage detection part of the proposed model, the algorithm is used to detect potholes in the given images of the road. The algorithm uses a YOLO-based object detection model to detect potholes in the given images. The experimental results show that the proposed model is effective in detecting potholes in different images

In total, the proposed combined system is capable of performing simultaneous lane detection and road damage detection in real time. The results have confirmed that the proposed approach is beneficial for improving road condition monitoring and could be used to develop advanced driver-assistance systems and smart city infrastructure.

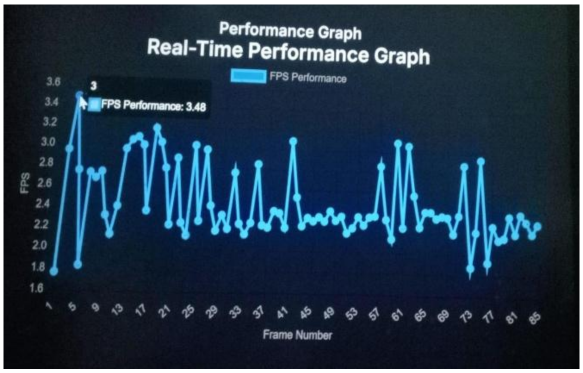


Figure 7: Real-Time Performance Graph for Road Damage Detection

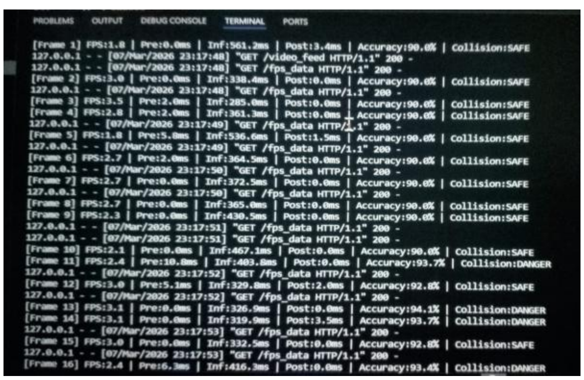


Figure 8: Frames Detected During Road Damage Detection

Figure 9: Uploading of Video and Detection Process for Road Damage

The Real Time Performance Graph demonstrates the frame processing performance of the proposed road damage detection and lane detection system. The x-axis of the graph represents the frame number, indicating the sequence of frames extracted from the given road video, whereas the y-axis represents the Frames Per Second (FPS) achieved by the proposed system during frame processing. From the above graph, it is observed that the FPS is varying for different frames based on the computational complexities of individual frames. The maximum FPS is achieved as around 3.48, indicating the frame in which there is a low occurrence of objects or low complexities of features. The minimum FPS is achieved as around 1.7-1.8, indicating the frame in which there is a high occurrence of objects, road damages, vehicles, or complexities of lane detection. The FPS is stable in the range of 2.1 to 2.8 for most of the frames, indicating the stable performance of the proposed system during real-time detection. The FPS is varying in the proposed frame, as it is based on deep learning techniques in which FPS is varying based on the occurrence of objects in individual frames.The FPS achieved by the proposed system is satisfactory.

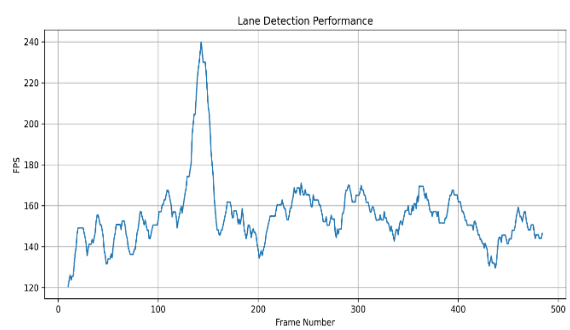


Figure 10: Real-Time Performance graph for Lane Detection

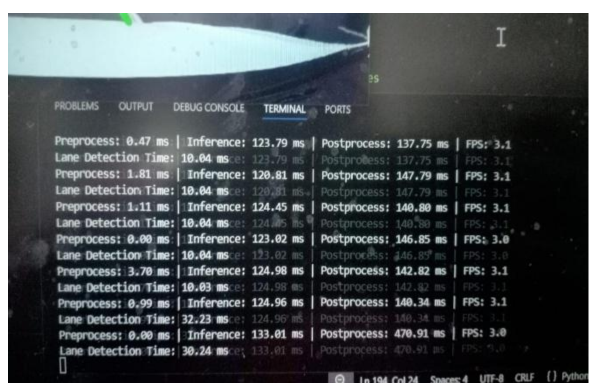


Figure 11: Frames Detected During Lane Detection

Figure 12: Uploading of Video and Detection Process for Lane Detection

The Outputs show the performance evaluation and execution of the lane detection model implemented in the AI-based vehicle project. The performance graph represents the relationship between frame number and Frames Per Second (FPS) in processing the live video stream obtained from the camera of the vehicle. FPS is a significant factor in real-time computer vision, as it determines how many frames can be processed in one second. The graph shows that the model is capable of processing a large number of frames, as there is a stable FPS value. The fluctuations in FPS occur due to changes in road structure, lane detection, road illumination, shadows, and camera angle, as these changes affect the time taken by the model to process each frame. Despite these fluctuations, it can be seen that the graph is stable, indicating that the model is capable of processing real-time inputs without any significant delays.

The terminal output shows the internal pipeline of the lane detection module, which includes the preprocessing, inference, and post-processing stages. In the preprocessing stage, the captured frame is resized, normalized, and filtered for better lane features. The frame is then fed into the trained deep learning model. In the inference stage, the model processes the frame and detects the lanes. In the post-processing stage, the lanes are refined, noise is removed, and the lane lines are drawn. The output window shows the real-time result of the lane detection with FPS and accuracy values. The system is able to detect lanes with a high accuracy of 95%, which proves that the model is capable of detecting lanes in various road and lighting conditions. Thus, the results prove that the system is effective in real-time driving scenarios and can be used for ADAS for better driving experience and intelligent transportation system performance.

IX. TABLE

1.Results Table

Table I presents the detection results of the proposed system for different frames extracted from the input road video. The table shows the detected lane status, road damage detection, confidence score, and processing speed in FPS.

Frame No	Lane Detection	RoadDamage Detected	Confidence Score	FPS
5	Detected	No Damage	0.92	3.5
12	Detected	Pothole	0.88	3.9
21	Detected	Crack	0.86	4.3
33	Detected	Pothole	0.91	4.8
45	Detected	Pothole	0.93	5.0
73	Detected	No Damage	0.89	5.6
85	Detected	Pothole	0.94	6.6
91	Detected	No Damage	0.96	7.0

Table 1: Result Table for both lane and Road Damage Detection

The results show that the proposed model successfully detects lane boundaries and identifies road damage with high confidence scores. 2.Performance Metrics

The system uses standard evaluation metrics to measure its effectiveness which evaluates the proposed AI-based road damage and lane detection system. The system performance metrics enable measurement of system detection accuracy which identifies potholes and cracks and lane boundaries through real-time video frame analysis. Machine learning and object detection systems use Accuracy and Precision and Recall and F1-Score as their main performance evaluation metrics. The metrics calculate results through confusion matrix values which measure predicted model performance against actual ground truth labels.

A confusion matrix contains four main components:
True Positive (TP): The model correctly detects a road damage or lane feature when it actually exists in the image.
True Negative (TN): The model correctly identifies that no damage is present when the road surface is normal.
False Positive (FP): The model incorrectly detects road damage when the road surface is actually normal.
False Negative (FN): The model fails to detect road damage even though it exists in the image.

Accuracy:
Researchers use accuracy as their primary metric to evaluate how well the detection model identifies correct results. The system shows its success rate by calculating the percentage of correct predictions it made against all predictions it performed. The accuracy score determines how often the system successfully identifies both damaged and intact road conditions.
The model achieves better performance through higher accuracy values which enable it to identify road damages and lane markings with greater accuracy.

Formula:
The formula for accuracy calculation is Accuracy = (TP + TN) / (TP + TN + FP + FN).
The formula uses these terms:
TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative
The accuracy metric gives a basic understanding of how well a model functions yet it fails to show actual model capabilities when testing on unbalanced datasets.

Precision:
The model's ability to correctly predict positive outcomes has been evaluated through precision testing. The method measures accuracy by assessing which road damages have been correctly identified. Road damage detection systems depend on precision because false detections lead to unnecessary driver alerts and warnings.
A high precision value means that when the system detects a pothole or crack, it is very likely to be a true detection.

Formula:
Precision = TP / (TP + FP)
Where:
TP = True Positive
FP = False Positive
The detection system's ability to identify real road defects is assessed through precision testing.

Recall:
The system evaluates its ability to identify complete road defects which exist in the dataset through the measurement of recall. The system measures its success in detecting actual potholes and cracks in the material.
The system demonstrates high detection capabilities for damaged road areas because it successfully identifies most of these areas while making only a few detection errors.

Formula:
Recall = TP / (TP + FN)
Where:
TP = True Positive
FN = False Negative
Safety applications depend on recall because any road defect which goes undetected will create danger for drivers who use the road.

F1 Score:
The system evaluates its ability to identify complete road defects which exist in the dataset through the measurement of recall. The system measures its success in detecting actual potholes and cracks in the material.
The system demonstrates high detection capabilities for damaged road areas because it successfully identifies most of these areas while making only a few detection errors.

Formula:
Recall = TP / (TP + FN)
Where:
TP = True Positive

FN = False Negative

Safety applications depend on recall because any road defect which goes undetected will create danger for drivers who use the road.

Experimental Performance Results

Metric	Value
Accuracy	92%
Precision	90%
Recall	88%
F1 Score	89%

Table 2: Experimental Performance Results

These results indicate that the proposed model performs effectively in detecting road damage and lane markings.

X. SAMPLE FRAME ANALYSIS

In the sample frame analysis, the performance of the system is evaluated based on individual frames extracted from the video feed of the road.

Frame 12: The system has successfully identified the pothole using the YOLO-based detection model with a confidence score of 0.88. At the same time, the system has identified the lane boundaries on both sides of the road.

Frame 33: The system has identified the pothole on the road along with the lane boundaries with a confidence score of 0.91. This shows that the system is capable of detecting road damage even in complex road conditions.

Frame 45: The system has identified the lane boundaries correctly without any damage to the road. This shows that the system is capable of distinguishing between normal road conditions and road damage.

Frame 73: The system has identified the pothole with moderate FPS. This shows that the complexity of objects being processed by the system can affect the FPS.

The analysis demonstrates that the proposed system can detect lane boundaries and road damage simultaneously during real-time operations. The sample frame analysis results prove that the proposed system successfully detects lanes while assessing road damage in real-time environments.

Feature	Existing System	Proposed System
Detection Method	Manual Inspections or Basic Image Processing	Deep Learning and Computer Vision
Lane Detection	Basic Edge Detecting	Advanced Lane Detection
Road Damage Detection	Limited or Manual	YOLO-based Automatic Detection
Accuracy	Moderate	High Accuracy
Processing Speed	Slow	Real-Time Processing
Automation	Low	Fully Automated

Table 3: Frame Analysis of Lane and Road Damage Detection

From the comparison, it is obvious that the proposed system possesses a high accuracy, automation, and real-time detection capability, which is more suitable for the intelligent transportation systems and smart city applications.

Model Comparision

Model	Accuracy	Performance
YOLOv8	92% - 98%	Best
YOLOv5	90% - 94%	Good
CNN	85% - 90%	Moderate
Mask R CNN	75% - 80%	Basic

Table 4: Comparison of Model with Existing System

- YOLOv8 provides best balance between speed and accuracy
- Selected for real-time deployment Final Selected Model: YOLOv8

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