Smart Vehicle Routing on Damaged Routes with Deep Learning

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***Abstract*—The increase of potholes and road surface damage poses important challenges to traffic safety and urban infrastructure management. Traditional detection methods rely on either manual inspection or cloud-based processing, which has more latency, cost, and scalability limitations. This paper proposes a real-time deep learning system for efficient road navigation using YOLOv4-tiny for pothole detection. The model classifies detected potholes based on its severity like small, medium, large and suggests the optimal navigation directions like left, center, right based on severity density in each region of the frame. The system integrates a web user interface built with Flask, which enables users to upload images or videos or use real-time webcam feeds for detection. Preprocessing techniques such as resizing, normalization, and data augmentation were applied to optimize model training. Evaluation metrics including Damage Density (DD), Route Efficiency Score (RES), and F1 Score validate the system's performance. The proposed solution achieves high detection precision and recall, ensures low-latency inference without requiring cloud connectivity, and demonstrates significant improvements in road safety decisionmaking. By integrating real-time detection with visual analytics and direction guidance, the system act as a tool for traffic management and preventive road maintenance.**

Keywords—Deep learning, Artificial Intelligence, Road Damage Detection, Cloud Computing, Computer Vision, Data Transmission, Road Navigation.

I. INTRODUCTION

Road maintenance is an essential part of a country's infrastructure to provide safety and reliability in transportation. Conventional approaches make use of costly survey cars mounted with laser line-scan and 3D cameras that are not within the reach of budget-constrained local governments. To counter this, AI-based solutions, specifically deep learning models, provide cost-efficient alternatives. Smartphone photography, driven by Convolutional Neural Networks (CNNs), has become an effective alternative with more than 90% detection accuracy for pavement distress. They are capable of detecting cracks, potholes, and surface defects with high accuracy, accelerating road inspections and maintenance.

CNNs can handle large amounts of data at high speeds, greatly increasing the speed and accuracy of road damage detection compared to manual observation. With real-time road condition assessment, such systems allow for quicker identification and repair of infrastructure deterioration. Machine learning adds to the mix with predictive maintenance, allowing the authorities to predict and repair road deterioration before it worsens lower repair costs, longer road life, and improved commuter safety.

The research utilizes YOLOv4-tiny, a lightweight and real-time capable object detection model, in classifying road damage based on size. The YOLOv4-tiny model is used for edge devices with limited computational resources, making it ideal for real-time inference without relying on cloud infrastructure. Our approach combines real-time video analysis, severity classification, and navigation suggestions (left, center, right), providing a low-latency, scalable, and practical solution for smart traffic systems and road safety.

II. LITERATURE SURVEY

The Global Road Damage Detection Challenge (GRDDC) is concerned with the automation of image-based road damage detection. Ensemble learning is identified as the best approach, with key points of success and where improvement is needed [1]. Road surface damage detection has achieved good accuracy, but most techniques are not capable of classifying damage types. A CNN model based on a self-collected dataset fills this gap, exhibiting high precision and fast execution on both GPU servers and mobile phones [2].

A 3D Reduced Inertial Sensor System (RISS) integrated GPS increases positioning precision. With the aid of onboard Controller Area Network (CAN) and Kalman Filtering (KF),

the system performs better in terms of accuracy and reliability than conventional techniques [3]. Precise positioning is needed in autonomous vehicles, but GNSS receivers are hindered by environmental interference. Reliability is improved by a Light Detection and Ranging (LiDAR) based odometry, and it can achieve a decrease in error with respect to single inertial solutions under simulated road tests [4].

Precise and safe navigation is a requirement for land and autonomous vehicles. GPS and GNSS are used as basic navigation sources, with serving as a fail-safe. Integration of GNSS-RISS was proposed to reduce drift errors, enhancing accuracy in urban canyons with distorted GPS signals [5]. Free and standardized geodata are vital in robot navigation. Open Street Map (OSM) offers large-scale spatial information, such as roads, points of interest, and traffic, which are utilized for localization and path planning for the first time. Based on OSM navigation, precision and autonomy in outdoor experiments are boosted [6].

Autonomous driving in rural environments is problematic because dense pre-built maps are impractical. Sparsityenabled hybrid method combines sensor-based real-time perception for local motion with sparse topological maps for global localization. Least-squares estimation of residuals enhances reliability so that high-speed navigation can be carried out without previous mapping. Real-world tests verify its efficiency in unstructured environments [7]. Road detection is still problematic in noisy environments, influencing autonomous driving precision. An integrated method that employs edge detection and road area extraction enhances performance in changing lighting and blurry edges. Segmentation, Hough efficiency and is highly effective in urban environments [8]. A vision-based road detection system guarantees real-time processing on a massively parallel hardware platform. Expectation-driven image segmentation and multiresolution stretching are adopted to improve detection efficiency with low costs. A deep learning solution projects LIDAR point clouds to top-view images for road detection. Pixel-wise segmentation is done by a fully convolutional neural network, with state-of-the-art performance and real-time inference [9].

Enhancements in visual image-based road detection continue to struggle with challenges such as illumination variations and motion blur. LiDAR information, which is less prone to these problems, provides more accurate detection but creates spatial mismatches when fused with visual information. Prior Learning Assessment & Recognition (PLARD) solves this by mapping LiDAR into visual space and fusing features using a cascaded framework, performing better than state-of-the-art models on urban experiments [10]. Automated detection of pavement distress is vital for its timesensitive maintenance. Vision inspection based on deep learning utilizes models such as CSPDarknet53 and Efficient Net, which were trained using road images from various nations. Performance analysis on IEEE datasets illustrates enhanced precision-recall metrics, optimizing computerized road maintenance policies [11].

CNNs are conventionally used for low-dimensional grids such as images but find it difficult to deal with highdimensional irregular structures. A generalized CNN method based on spectral graph theory allows efficient, localized convolutional filters with computational efficiency. Experiments on MNIST and 20NEWS validate its efficacy in learning graph-based features, pushing deep learning into nonEuclidean spaces [12]. A new vehicle localization technique combines visual odometry with OpenStreetMap data to improve accuracy. By integrating map information into a Monte Carlo Localization algorithm, it minimizes visual odometry drift. Experimental verification proves better performance compared to traditional visual odometry, providing better positioning for autonomous vehicles [13].

An AI-based road damage detection technique from UAV images and deep learning enhances efficiency compared to human inspection. YOLOv4, YOLOv5, and YOLOv7 are trained on ensemble datasets, with YOLOv7 attaining, showing UAV-based AI potential for infrastructure monitoring [14]. Pavement distress detection is important for safety but restricted by manual inspections. A boosted YOLOv5 model incorporating a Generalized-FPN enhances feature fusion, enhancing accuracy for large-scale distress detection. Utilizing periodically refreshed street-view photographs, the method facilitates scalable urban road maintenance [15].

A deep learning method finds road defects such as potholes and cracks by analysing 10,828 images. YOLOv7 processes live images on an Nvidia Jetson Nano, with data transmitted over 5G to MongoDB. The technique performs 93.3% mAP, 87.8% recall, and 93.2% precision and is effective in real-time defect detection [16]. Strong road safety systems are needed for autonomous vehicles. This research compares one-stage (YOLO, SSD) and two-stage (Faster RCNN) deep learning models for detecting damage and classifying road surfaces. This emphasizes the need to conduct more research to enhance the safety and efficiency of autonomous driving [17].

However, many existing systems either depend on highend GPU clusters or cloud processing, leading to latency and implementation cost issues. Moreover, severity-based direction suggestions for immediate decision-making are rarely explored. Our work addresses these gaps by deploying YOLOv4-tiny and providing real-time navigation guidance based on pothole severity.

III. EFFICIENT ROAD NAVIGATION

YOLO reframes the task of object identification as one regression problem. It runs through the input image once and subdivides it into a grid with S x S cells. For each cell, it predicts B bounding boxes together with a confidence score as a measure of the Intersection over Union (IOU) with respect to the ground truth bounding box. It also classifies if an object is likely to exist in the bounding box predicted. Application Programming Interface (API) are created for different functions such as adding, deleting, displaying, and checking objects.

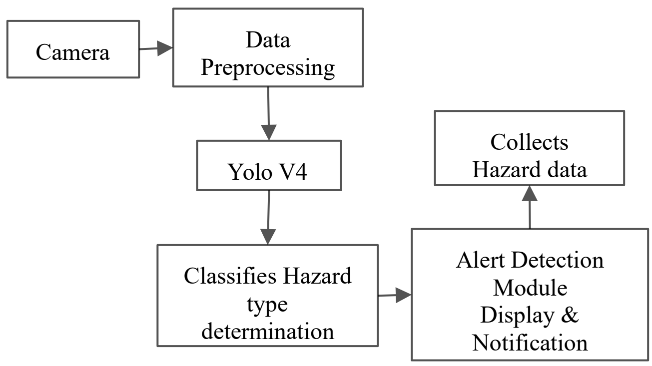


Fig. 1. System Architecture of Effective Road Navigation

The UI communicates with the backend through API calls, which invoke the respective functions. Video Capture object is used for capturing video. After the capture process starts, every video frame is decoded and translated into a series of images to be processed further. The overall software features are directly related to the specified requirements and the organized sequence of sophisticated device capabilities. In the architectural design stage, several web pages and their relationships are mapped and organized. The main software elements are examined, decomposing them into processing units and idea records. The system's design specifies various modules, illustrating their functionality and the relationships between them to guarantee smooth integration.

The above figure 1 shows the system records live video through a camera, processes the video through YOLO to detect hazards, and decides the type and location of hazards. Detected hazards are shown through alerts and sent to the backend for data handling and navigation commands. Table 1 describe the comparison of traditional method and proposed system.

TABLE I. COMPARISON TABLE

Feature/Criteria	Traditional Methods	Proposed System
Deployment Platform	Cloud or Offline	Edge+ Web-based

Pothole Size Classification	No	Yes (Small, Medium, Large)
Real-time Navigation Support	No	Yes
Hardware Requirement	High (GPU, 3D scanners)	Low (Yolov4-tiny on CPU)
Data Visualization	Limited	Heatmaps, RES, graphs

a. System Modules

The modules that are used in efficient road navigation are listed below.

A. YOLO Object Detection Module

YOLO (You Only Look Once) simplifies object detection as a one relapse problem, enhancing object detection speed and accuracy in images. The entire image is divided into an S x S grid. Every framework cell predicts numerous bounding boxes, a certainty score as the Crossing point over Association (IOU) with the ground truth, and the probability the bounding box contains an object. The model is learned on a set of broken and unbroken streets to detect patterns characteristic of street damage. With a CNN involving a sequence of convolutional layers and lingering blocks, just go for it identifies and segments broken areas precisely.

B. API Integration Module

APIs interact with communication between the UI and backend system, performing operations related to street condition the board. The module facilitates real-time sharing of information, where detection results of the YOLO model can be retrieved, processed, and shared with other systems, including mapping services or traffic monitoring systems. The API provides secure data transfer, optimization of the requestresponse cycle, and scalability for mass deployment.

C. Video Capture and Processing Module

The module captures and processes video footage of roads to identify and follow the damaged areas in real-time. The module relies on camera installations on roadsides, on poles, or on vehicles, recording road conditions in real-time. The module enhances video quality by employing pre-processing techniques like frame extraction, noise removal, and edge detection. The pre-processed frames are fed into the YOLO model to identify objects for accurate detection of road damage, such as potholes, cracks, and deformations.

D. Data Handling and Visualization Module

Data Handling and Visualization Module takes the output of the detection from the YOLO model and incorporates them into a navigation system. The module structures detected data into a database, separating road damage by severity, geolocation, and classification category. Heatmaps, dashboards, and geospatial maps are used to visualize insights into the road conditions. The module provides decisionmakers the ability to identify trends, plan priorities for maintenance activities on the roads, and enhance public safety.

E. Navigation Enhancement

Based on the roadway shortcomings identified, the Navigation Enhancement Module maximizes route recommendations to avoid dangerous portions, ensuring road safety and navigation efficiency. The module interacts with GPS and mapping service providers to provide real-time rerouting recommendations, preventing traffic discontinuity and reducing the mechanical deterioration of vehicles. Employing machine learning algorithms, the system maximizes real-time route recommendations in response to changing road conditions. Finally, the module maximizes the trip experience by reducing delays and the rate of accidents related to dangerous road conditions.

b. Model Training

The training modules are listed below as follows.

A. Dataset Preprocessing

The action of preparing image data for use in machine learning algorithms or other applications that are pertinent is referred to as "image data preprocessing," and the name "image data preprocessing" refers to this act. Typically, the procedure entails undertaking a series of sequential actions aimed at enhancing the usability and precision of the image data for analytical objectives. These actions involve the cleaning, standardisation, and transformation of the data. The preparation of image data is an essential step in both image analysis and deep learning. This is because the preprocessing of image data has the ability to dramatically impact the accuracy and effectiveness of the final models. In the process of preparing image data, the following methods are widely utilised.

B. Resizing

The act of adjusting the proportions of a picture such that it fits into a container of a certain size. The processing and comparing of images may be made much easier if they are all of the same size across a collection.

C. Cropping

Cropping an image is cutting off parts of the image that are unnecessary or unimportant. This is done so the picture may be examined more closely. Employing noise reduction techniques can potentially decrease the level of noise present in an image, thereby potentially enhancing the precision of the analysis.

D. Normalisation

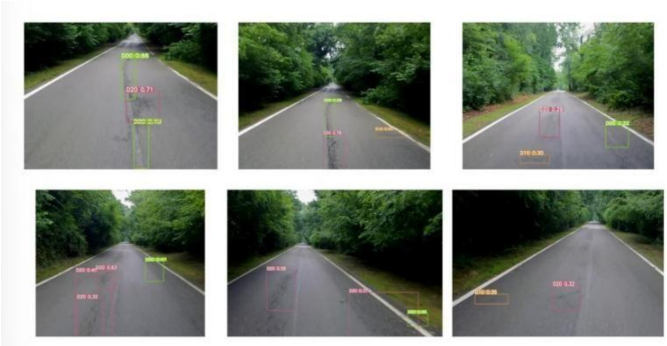
Normalisation is a procedure that involves altering the pixel values of a picture so that they correspond to a predefined range. This range is often between 0 and 1, but it may be any number in between. The data can be processed and compared more easily if they are standardised beforehand.

E. Augmentation

The term "augmentation" refers to the process of producing extra images by applying a variety of modifications to the base image, such as rotating it, flipping it, or adding noise to it. This list is not exhaustive. The expansion of the dataset can increase the amount of the dataset as well as the accuracy of the final models.

F. Feature Extraction

Feature extraction involves the detection and extraction of important characteristics from picture data. These features may include edges, textures, and forms, but are not restricted to just those three categories. For the purpose of completing this job, many algorithms, such as the Sobel operator and the Canny edge detector, may be applied.



G. Data Cleaning

The manipulation of image datasets entails a multitude of procedures, among which is commonly referred to as "data cleansing." This phase entails identifying and eliminating any information that has been deemed to be erroneous or invalid. Ensuring the consistency and error-free nature of the data can enhance the precision of the ultimate models. The figure 2 shows a sample image detection of the model.

Fig. 2. Image detection of sample data of the application

c. Performance Analysis

During the phase of data preprocessing, it can be observed that the categories that were previously classified as 'other' classes in the Pascal VOC formatted annotation files are transformed into the 'None' category in the YOLO formatted text files subsequent to the conversion process.

Consequently, the remaining classes are transformed into null values, rendering them unsuitable for the purposes of training. Under such circumstances, it is necessary to eliminate non-valuable data from the text files through cleaning. This cleaning procedure is implemented for all experiments. The above figure 3 shows the way application allows users to select and choose a detection method. The system then processes the input and displays the detection

Fig. 4. Samples of detection from the real-time video as a demonstration of using the application

The above figure 4 shows the sample of detections from real-time video and its classification done using the detection process.

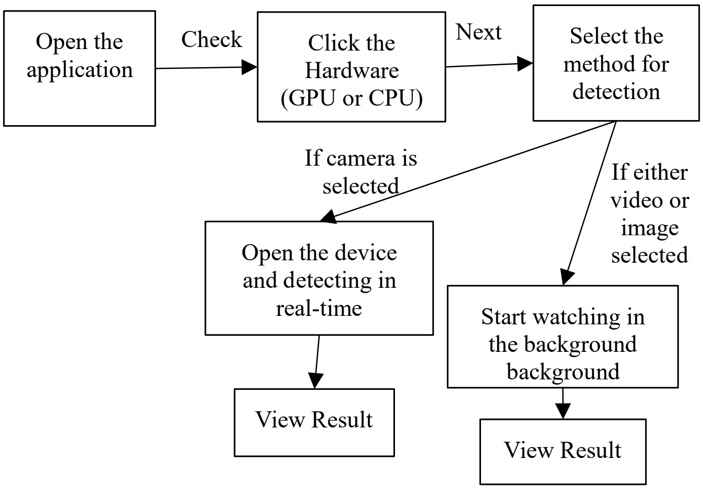


Fig. 3. Application Pipeline diagram

results.

d. Real-Time Implementation

The execution of this software yielded a randomised video sourced from the internet as a sample demonstration. The video feature is selected within the context of utilising this particular application. Upon analysing the video, the ensuring outcome was obtained. Several samples of snippets have been gathered.

IV. RESULTS AND DISCUSSION

The strategy of YOLO of regarding object identification as a solitary relapse issue and dissecting the picture in one pass works on both speed and exactness. The system efficiently determines the damaged areas picture into a framework and foreseeing bounding boxes and item probabilities.

A. Damage Density (DD)

Damage Density quantifies the amount of road damage per unit length of a route. The number of detected damages (e.g., potholes, cracks) along a route segment, and L is the length of the route segment (e.g., in kilometers). This metric is valuable for assessing the overall condition of a road. The DD is shown in equation 1.

$$DD = N / L \qquad (1)$$

Where N is number of detected damages and L is length of route segment. The below figure 5 represents the graph of damage. Route Efficiency Score calculates the percentage improvement in travel distance (or time) achieved by using the deep learning-based navigation system. TD_baseline is the travel and TD_optimized is the travel distance with the optimized route based on damage prediction. The RES shown in equation 2. The above figure 6 represents the graph of route efficiency score. RES = (TD_baseline - TD_optimized) /

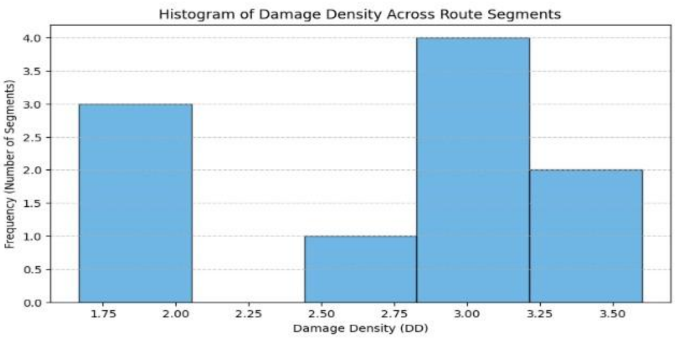


Fig. 5. Damage Density of route

B. Route Efficiency Score (RES)

distance without the optimized route,

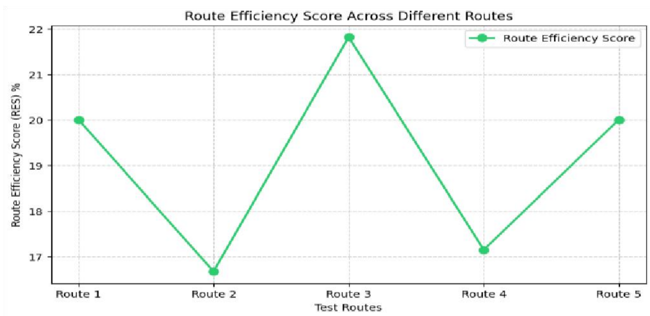


Fig. 6. Route Efficiency Score

C. F1 Score

The F1 score is the harmonic mean of precision and recall. Precision is the ratio of correctly identified damages to the total damages predicted by the model, while recall is the ratio

TD_baseline * 100

(2)

of correctly identified damages to the total actual damages present.

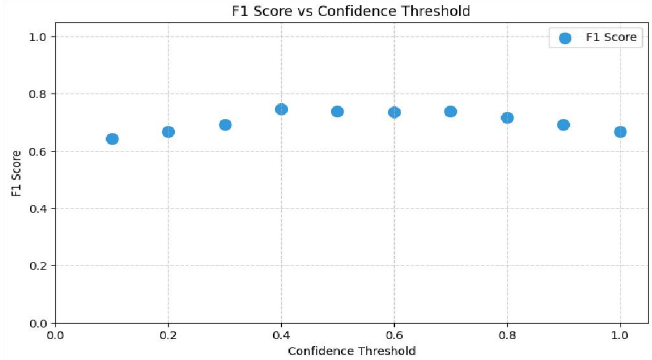
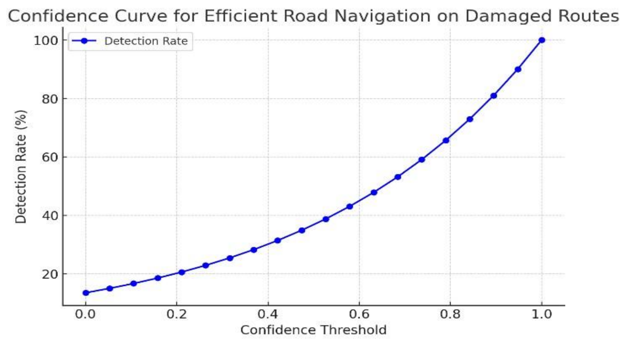


Fig. 7. F1 Score based on the Threshold

$$F1 = 2 * (Precision * Recall) / (Precision + Recall) \qquad (3)$$

D. Confidence Curve

The plot illustrates the effect of higher confidence threshold in lowering the detection rate and indicating the trade-off between precision and recall. The above figure 8 shows confidence curve for the Effective Road Navigation on Damaged Paths.



F1 score shown in equation 3. The above Figure 7 shows the F1 score vs the confidence threshold.

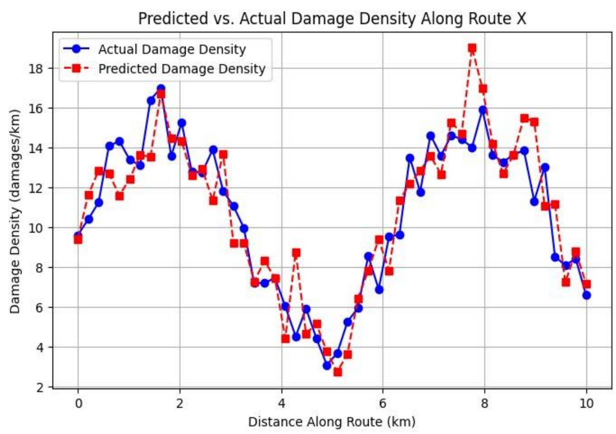


Fig. 8. Confidence Curve

E. Predicted vs Actual Damage

The chart of figure 9 illustrates the model's predictive performance in predicting road conditions and can be utilized to determine routes upon which the model excels or requires improvement.

Fig. 9. Predicted vs Actual Damage

V. CONCLUSION

Efficient Road Navigation is capable of efficiently enhancing road damage detection accuracy and navigation through deep learning techniques, i.e., the YOLO object detection framework. Through optimizing dataset preprocessing, utilization of augmentation techniques, and improving the ability of the model to extract features, Efficient Road Navigation has been able to significantly enhance detection accuracy and recall. Additionally, the use of realtime video capture and processing modules ensures the system is in a position to evaluate road conditions in real-time, thus making it a very effective and trustworthy solution.

Unlike previous models current approach minimizes latency by the use of edge computing which helps in achieving faster and better real-time detection. This technology offers responsive and smooth user interface, thus rendering the system flexible and scalable to different road conditions. In addition, the presence of the API facilitates secure data sharing with navigation and traffic observation services, thus enhancing road safety in general. The live deployment of Efficient Road Navigation model has shown robust reliability in detecting road hazards and low false positive rates. The performance of the system is also added by metrics like Damage Density, Route Efficiency Score, and F1 Score, which show robust improvements over existing methods. A solution, through the combination of deep learning methods with smart navigation, offers a robust and viable solution to road safety and maintenance enhancement.

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