Automated Pavement Distress Detection and Classification using Convolutional Neural Network with Mapping

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***Abstract*— This research paper presents an automated system developed using Jetson Nano and the YOLOv5n6 model for efficient and real-time detection and classification of pavement damage. The system offers a promising solution for transportation agencies in countries with extensive road networks, such as the Philippines, by reducing the need for manual inspections and streamlining maintenance efforts. By leveraging deep learning techniques, the proposed system demonstrates high accuracy in identifying various types of pavement damage, including cracks, alligator cracks, and potholes. The system's deployment on Jetson Nano provides efficient processing capabilities, enabling real-time analysis of video feeds from road cameras or mobile devices. The results of comprehensive evaluations indicate the system's adaptability to varying environmental conditions and its potential for large-scale implementation. The automated system contributes to cost savings, improved road safety, and enhanced management of pavement quality.**

Keywords—pavement distress, pavement distress classification, road infrastructure, pavement distress mapping, deep learning

I. Introduction

Roads are essential for economic development and provide social advantages by connecting people to job opportunities, social services, healthcare, and education. However, despite the construction of numerous road networks, congestion and overloading are prevalent in many areas. Factors such as natural wear and tear and human activities contribute to the deterioration of road surfaces, leading to issues like potholes, cracks, and unevenness. These problems increase fuel costs, prolong travel times, and pose risks to road safety. Detecting and addressing road distress at an early stage is crucial to prevent further damage and ensure safe and efficient transportation.

To address this challenge, Fakhri and Dezfoulian (2017) emphasize the importance of regular pavement assessment in road network maintenance and rehabilitation [1]. They highlight the significance of various assessment techniques, including visual inspection, manual surveys, and automated systems. Automated systems, leveraging technologies like image processing, computer vision, and machine learning, offer benefits such as efficient data collection and objective assessments. These systems enable the timely detection of road distress, facilitating prompt interventions before conditions worsen or become hazardous. By implementing accurate pavement assessments, road infrastructure can be made safer and more durable.

The proposed automated road distress detection, classification, and mapping system aim to improve the efficiency of road quality assessment. It includes the detection of distress, classification based on severity, and identification of different road surface types. Real-time mapping and monitoring of road quality are also incorporated into the design. The system utilizes a car-mounted camera to capture road conditions, with the coverage dependent on the camera's angle and placement. While the testing and analysis are limited to the city of Tanauan, the insights gained from this project can assist national specialists in evaluating road conditions.

A. Pavement Quality

It is important to choose a high-quality paving solution when constructing a road. The quality has a direct influence on how long and how effectively the asphalt surfacing will endure the effects of time, weather, and frequent use. High-traffic roads and parking lots in harsh weather conditions demand asphalt mixtures.

According to an article, road mishaps are responsible for the deaths of around 7,000 Filipinos each year, as well as the injuries of thousands more [2]. These statistics come from the World Health Organization (2021). Approximately 79 percent of these incidents result from mistakes made by drivers, 11 percent are due to malfunctioning cars, and 10 percent are due to poor road conditions and inadequate road maintenance. In most cases, the cause of these mishaps may be traced back to the driver's carelessness. Sometimes, drivers aren't the only ones to be blamed for accidents. A shocking number of automobile accidents occur yearly because of unsafe and deteriorated road conditions. Therefore, to promote road safety in our nation, the government's Department of Public Works and Highways should regulate the country's road infrastructures in a much faster way to avoid accidents that shouldn't happen in the first place if the road had been maintained adequately.

Asphalt must be stiff and resist distortion but also flexible and crack resistant. Stiffness and resistance to deformation allow asphalt to handle vehicle pressure; flexural strength prevents damage from contrasting pressures. The Philippines now has two kinds of asphalt: hot mix asphalt and cold mix asphalt. Hot mix asphalt consists of heated sand, gravel, and asphalt cement. Using this asphalt requires heating the mix between 300°C and 500°C before shipping and laying it at the desired location.

On the other hand, cold-mix asphalt is frequently used for repairs and minor patches. This type of mixture does not need to be heated. Bags of cold mix asphalt can be poured straight upon potholes or cracks to prevent the damage from spreading. According to the Department of Public Works and Highways (DPWH), the acceptable IRI (International roughness index) for asphalt roads shall be less than 3.0 m/km for National Primary Road [3].

B. Monitoring and Maintenance of Asphalt Road

The Department of Public Works and Highways (DPWH) is responsible for the planning, design, construction, and maintenance of national highways in the Philippines. Currently, road condition monitoring is conducted through manual inspections performed by surveyors. These surveyors visually assess road distress and record their findings, including the location and classification of the distress. Manuals are used to ensure consistent data collection, providing standards for the identification and severity rating of road defects.

Previous research in 2018 from alumni of FAITH colleges, involved an interview survey with DPWH to gather insights into road condition evaluation [4]. The evaluation process, known as Local Road and Bridge Inventory and Condition Survey (LRBICS), relies on visual assessments by engineers. Road conditions are categorized as good, fair, poor, or bad based on the observed imperfections. The LRBICS manual draws from existing inventory, condition, and planning manuals used nationwide.

However, these manual inspection techniques have limitations. They require specialized expertise and involve field trips that can be time-consuming, expensive, and potentially hazardous. Recommendations include the use of the Road Condition (ROCOND) manual by the Department of the Interior and Local Government (DILG) for LRBICS surveys. This manual incorporates references from various DILG and DPWH manuals and involves a survey team consisting of personnel from the planning, design, and maintenance divisions.

While manual surveys are effective, practical, and widely used, they have drawbacks. They are costly, time-consuming, and reliant on the competence of the surveyor. Manual inspections also pose risks to surveyors working on highways and can disrupt traffic flow. Mr. Mario Sianquita, the Maintenance Point Person of the DPWH, highlighted the labor-intensive nature of manual inspections and expressed the need for an automated system to make the process faster and easier.

In conclusion, there is a recognized need for an automated system to enhance the maintenance and monitoring of road pavements. The current manual survey approach, while effective, has limitations in terms of cost, time, accuracy, and safety. Developing an automated system would provide a faster and more efficient way to assess road conditions, ensuring timely interventions and improved road infrastructure management.

C. Proposed Automated Pavement Distress Detection Classification and Mapping System

The proposed automated road distress detection, classification, and mapping system are to be deployed to help Local Government Units (LGUs) in surveying road conditions. The design is featured to categorize cracks, rate road quality, assess whether a road is paved, and segment different asphalt road distresses such as cracks, alligator cracks, and potholes. Instead of physically examining roads, the suggested automated road distress detection will assist in monitoring, gathering, categorizing, and mapping road quality through real-time object detection based on different approaches to detect road distress.

II. REVIEW OF RELATED LITERATURE

This section contains a summary of the literature related to the theory and experiments carried out for this thesis.

A. Crack Detection

A study proposed by Lekshmipathy et al. (2020) presents two automated, cost-effective methods for evaluating pavement distress conditions. The first method involves smartphone sensor-based distress detection, using an Artificial Neural Network (ANN) to identify road defects [5]. The second method utilizes MATLAB coding for image processing to detect potholes, patches, and cracks from pavement video data. While both methods offer cost advantages and reasonable accuracy, the image processing approach is more effective than the vibration-based method, which detects distresses along the wheel path. The smartphone-based approach works day and night, while image processing requires artificial lighting at night. Combining methods could mitigate limitations and provide valuable insights into pavement conditions.

Abbas and Ismael's study (2021) also underscores the transformative potential of image processing in pavement distress detection, aligning with the trend of enhancing infrastructure management through technology [6]. Their approach streamlines distress categorization, demonstrating efficient and precise outcomes. The automated process offers enhanced safety, user-friendliness, and cost-effectiveness, positioning it as a promising alternative for conventional road measurements.

Du, Y., Pan, N., Zhang, X., Deng, F., Shen, Y., and Ke, H. (2020) employ a YOLO network-based approach to advance pavement distress detection [7]. Curating a dataset of 45,788 high-resolution images, each annotated with precise bounding boxes, they achieve a robust 73.64% detection accuracy and a processing speed of 0.0347s per image. Notably, their YOLO-based method outperforms Faster R-CNN by a factor of nine in processing speed and consumes only 70% of the time of SSD. Furthermore, their exploration of the model's adaptability to different illumination conditions underscores its strong performance under optimal lighting. This YOLO-based approach offers promising potential for accurate PD detection without manual feature extraction, presenting opportunities to enhance pavement management and rehabilitation efforts.

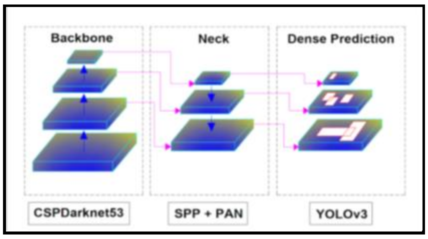


Fig. 2.1 The network architecture of YOLOv4

Sung-Sik Park et al. (2021) conducted research on pothole detection using different object detection frameworks, including YOLOv4, YOLOv4-tiny, and YOLOv5s [8]. They evaluated the performance of these frameworks in terms of real-time responsiveness and detection accuracy using a dataset of 665 photos capturing various types of potholes under different road conditions. According to the study findings, the mAP 0.5 of YOLOv4, YOLOv4-tiny, and YOLOv5s are 77.7 percent, 78.7 percent, and 74.8 percent, respectively. The results showed that YOLOv4-tiny achieved the highest mean average precision (mAP) score among the tested models.

In a comparative study conducted in 2022, the performance of various object detection algorithms was evaluated, including YOLOv5, YOLOv3, and YOLOv4 [9]. The study focused on assessing mean average accuracy (mAP) and frames per second (FPS) as performance metrics. The results indicated that YOLOv5 outperformed the other algorithms, exhibiting higher accuracy and faster processing speed. Based on these findings, the researchers developed a smartphone application called "ObjectDetect" using YOLOv5, aimed at assisting users in making incombered decisions while driving.

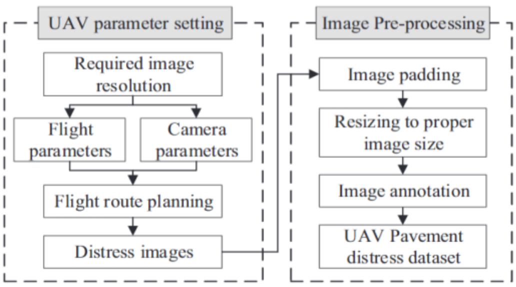


Fig. 2.2 Flowchart of UAV pavement distress image acquisition

Huang et al. (2022) proposed the use of a UAV equipped with a high-resolution camera for gathering pavement deterioration data [10]. They constructed a UAV platform and optimized flying parameters to ensure high-quality pavement images. The acquired photos were processed, labeled, and used to train three object detection algorithms—Faster R-CNN, YOLOv3, and YOLOv4. Comparisons were made, and YOLOv3 demonstrated the best prediction capabilities among the tested algorithms. Fig. 2.2 illustrates the flowchart of UAV pavement distress image acquisition, showcasing the setup and process of capturing pavement pictures using the UAV platform.


Fig. 2.3 Street View Object-Mapping

In 2018, Krylov, Kenny, and Dahyot introduced a methodology to automate detecting and geotagging stationary objects in street view images [11]. Their approach employed convolutional neural networks (CNNs) for object segmentation and depth estimation, integrated with a Markov random field model for geolocation. By combining depth estimation and the geolocation model, their method enabled triangulation, yielding accurate 3D coordinates for detected objects. Experimental validation demonstrated strong recall rates and precise positioning. This technique's integration of depth estimation and triangulation resonates with our pavement distress automation objectives, offering insights for similar applications in identifying pavement irregularities and improving infrastructure management.

III. Methodology

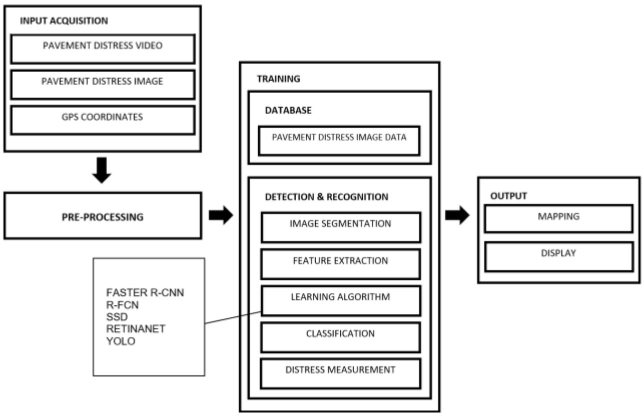


Fig. 3.1 Conceptual Framework

The research design focuses on constructing a system for pavement distress detection, classification, and mapping using image processing techniques. The design employs an input-process-output (IPO) model to conceptualize the system's architecture. The conceptual framework consists of four key processes: input acquisition, pre-processing, training, and output. These processes form the foundation of the design.

A. Input Acquisition

Image data needed for training and testing deep neural networks are collected using a camera interfaced with the microcomputer. The collected images are geotagged, which provides details on reference time and location.

B. Pre-processing

The acquired data are then pre-processed through four steps: (1) defining the bounding box regression; (2) cropping the bounding box regression; (3) image resizing; and (4)

Feature scaling. This process increases classification accuracy, given that it helps enhance features in the input.

C. Training

For recognition and detection tasks, deep convolutional neural networks efficiently handle image segmentation, feature extraction, classification, and categorization. In a Python application, this process is extracted from pavement distress inputs and utilized as the primary feature for classification in the object detection algorithm.

D. Mapping

The device, linked to a GPS module, executes real-time processes with simultaneous updates for practical use and visualization. Data is automatically registered if it meets the minimum accuracy threshold, along with the detected image's coordinates. Subsequently, a display showcases the detected items alongside reference GPS data.

E. Method of Data Collection

The researchers collected data from various sources, including relevant studies, literature, and IEEE papers, to ensure the accurate execution of their study on autonomous pavement distress detection, classification, and mapping. They also conducted an interview with professionals from the Batangas 3rd District Engineering Office to gather additional insights and recommendations for enhancing the design. This data and information enabled the researchers to develop a comprehensive framework for detecting pavement distress and plan the necessary system development for real-time implementation.

IV. TECHNICAL STUDY

A. Project Design

The proposed automated pavement distress detection and classification using neural network and mapping focuses on classifying different pavement distress classifications based on the given database of DPWH: crack, alligator crack, and potholes pavement. The project implements a classification device that records pavement distress using a camera module and a microcontroller with the use of Python and YOLO learning algorithms. A GPS module to embed the captured image with the exact location where it is taken. The project is implemented using Raspberry Pi placed inside the car, and a Raspberry Pi HQ Camera mounted on the car's front.

B. Block Diagram

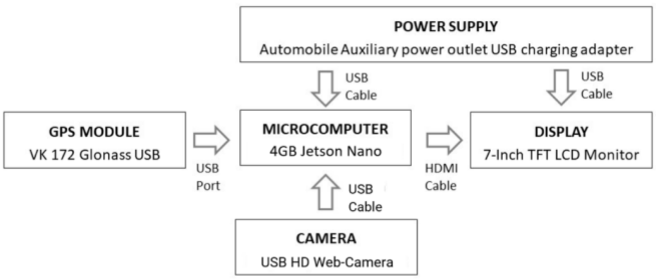


Fig. 4.1 Block diagram

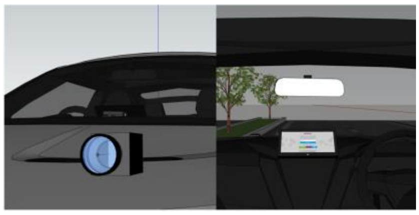


Fig. 4.2 3D Model

The input acquisition modules used in the design are the Raspberry Pi HQ Camera for capturing wider and higher-resolution pavement images, and the VK-172 USB GPS Module for geotagging the data with latitude, longitude, time, and date. The hardware setup is shown in Fig. 4.1 and 3D model in Fig. 4.2. The microcomputer processes the data by detecting and recognizing various pavement distress types such as cracks, alligator cracks, and potholes. To accomplish this, a dataset is collected from publicly accessible internet images and preprocessed to enhance crack features and optimize training and testing accuracy. After processing, the data is mapped, and the output displays the locations of the identified pavement distress pins.

C. Flowchart

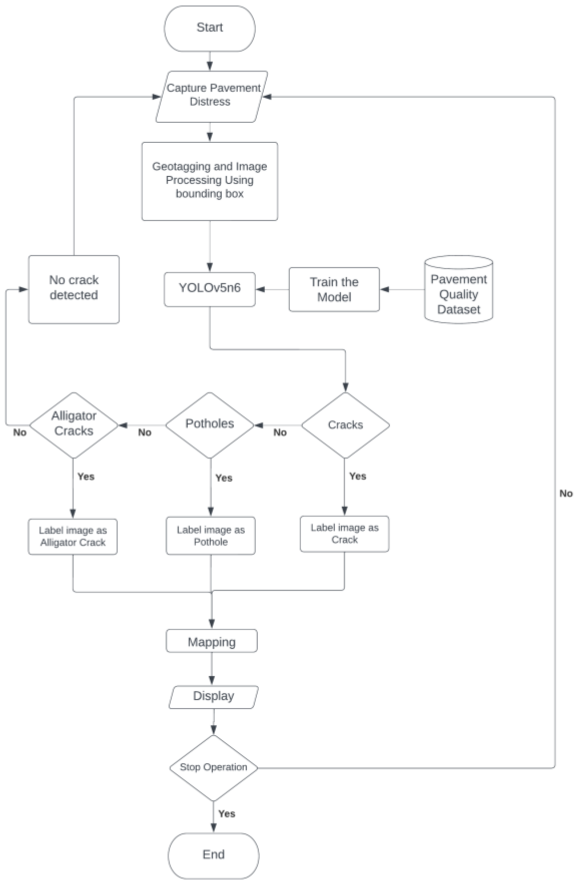


Fig. 4.3 Flowchart

During startup, all modules are powered on as depicted in Fig. 4.3. The camera begins capturing pavement images, which are then geotagged to determine their latitude and longitude. The processed images undergo a series of steps to accurately pinpoint their location. An algorithm convolves the processed image with the dataset, and a decision is made to classify it as cracks, alligator cracks, and potholes. If no pavement distress is detected in the acquired image, the system repeats the process for subsequent frames in the video stream. The collected and saved images are integrated into the database once a minimum accuracy is achieved during the detection phase. These images are displayed on an LCD panel, with the procedure executed simultaneously from vehicle acquisition to the cloud. At this point, a choice is presented to either stop the real-time pavement distress detection process or continue monitoring until the user decides to halt or shut down the system. The system persists in repeating its process until the user initiates the termination or shutdown.

D. Verification Plan

The study employed verification procedures such as detection calibration and actual road testing to ensure the designed automated distress detection system met the requirements. Data gathered from online sources, classified according to DPWH's records was used to train the detection model for accurate results. A prototype of the Automated Pavement Distress Detection (APPD) system was developed to validate the design and gather feedback. Through prototype testing on an actual road, with the camera mounted on the car's hood and connected to the microcomputer inside the vehicle, the system's functionality was assessed. A touch screen LED provided a user-friendly graphical interface. These verification procedures ensured the effectiveness of the APPD system design in accurately detecting and classifying various types of pavement distress.

TABLE IV. Dataset

Table 5.2 Classification Results using the images taken in Tanauan City, Batangas.

Classification	Image with Detection
Crack	
Alligator Crack	
Potholes	

V. RESULTS AND DISCUSION

The testing procedure encompassed a journey spanning from Tanauan City to Sta. Maria Santo Tomas Chapel in Batangas, Philippines. The experimental setup involved strategically placing the microcomputer, Jetson Nano, in proximity to the vehicle's occupants, while situating the camera externally to capture the surrounding environment. Additionally, a GPS u-blox device, with a refresh rate of 5Hz, was affixed atop the vehicle to ensure precise positioning data, which was duly verified throughout the testing phase.

The primary objective of the test entailed the utilization of the YOLOv5n6 object detection framework to identify and analyze various cracks encountered along the traveled route. The underlying aim was to assess the system's capability to replicate, in an automated fashion, the manual process traditionally employed for crack detection.

The RDD 2022 dataset provided a comprehensive collection of 47,420 road images from six countries. These images were classified into four categories of road damage. To ensure the effectiveness of the training process, a meticulous selection of images was carried out, emphasizing those with prominent features and minimal obstructions. Preprocessing techniques were then applied to optimize the training efficiency and overall model performance.

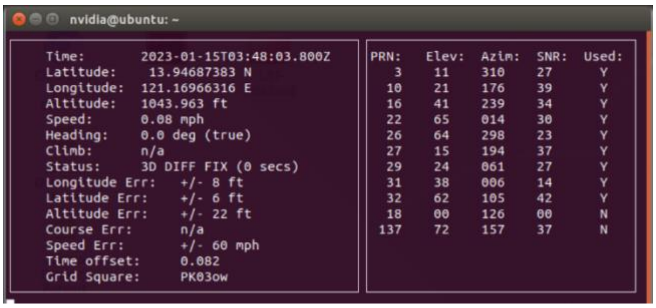
The training dataset was divided into three partitions: 70% for training, 20% for validation, and 10% for testing. Two models, namely YOLOv5s and YOLOv5n6, were evaluated for their speed and accuracy. While YOLOv5s showcased slightly higher accuracy, YOLOv5n6 emerged as the preferred model due to its superior detection and inference capabilities. The decision was driven by the need to prioritize real-time road usage scenarios, where swift processing speed takes precedence, while accepting a minimal trade-off in terms of accuracy.

Frames were sampled from the video footage at a rate of 14 frames per second (FPS). Subsequently, the extracted frames underwent classification detection to identify instances of road damage. The detected road damage instances were then cropped and stored in designated folders, categorized according to their respective classes.

Table 5.3 Accuracy, precision, recall, F1-Score values for the classification algorithm.

Class	n(truth)	n(classified)	Precision	Recall	F1 Score	Accuracy	Overall Accuracy
Potholes	17	20	0.75	0.88	0.81	88.33%	68.33%
Cracks	21	20	0.70	0.67	0.68	78.33%	
Alligator Cracks	22	20	0.60	0.55	0.57	70%	

Success rates, accuracy, precision, recall, and F1-Score values for classification algorithm were calculated and are presented in Table 5.3. The overall accuracy achieved by the implemented system was determined to be 68.33%. The system focused specifically on measuring the performance of classifying pavement distress.



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nvidia@ubuntu: ~
Time:           2023-01-15T03:48:03.800Z      PRN:  Elev:  Azim:  SNR:  Used:
Latitude:        13.94687383 N                  3     11    310    27     Y
Longitude:      121.16966316 E                 10     21    176    39     Y
Altitude:       1043.963 ft                    16     41    239    34     Y
Speed:          0.08 mph                       22     65    014    30     Y
Heading:        0.0 deg (true)                 26     64    298    23     Y
Climb:          n/a                            27     15    194    37     Y
Status:         3D DIFF FIX (0 secs)           29     24    061    27     Y
Longitude Err:     +/- 8 ft                    31     38    006    14     Y
Latitude Err:      +/- 6 ft                    32     62    105    42     Y
Altitude Err:      +/- 22 ft                   18     00    126    00     N
Course Err:        n/a                        137     72    157    37     N
Speed Err:         +/- 60 mph
Time offset:       0.082
Grid Square:       PK03ow
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Fig. 5.2 cgps -s info on GPS information

The implementation of the GPS module facilitated the acquisition of live-streaming communication between the system's object detection. Optimal conditions, such as clear skies and a high number of visible satellites, led to latitude and longitude coordinates with an accuracy of approximately 2.5 m to 5 m. Fig. 5.2 illustrates the GPS module's implementation, demonstrating an error margin of +/- 8 ft in longitude and +/- 6 ft in latitude when all channels were available. This level of precision could typically be achieved within a span of 5 minutes.

The integration of GPS data with the images allowed for the accurate mapping of pavement distress locations using a CSV file in Google Earth Pro. The mapped images effectively showcased the distribution patterns of different distress classifications, including cracks, potholes, and alligator cracks. Through a user-friendly Graphical User Interface (GUI), users were able to easily access the detected distress locations by utilizing the CSV file, which provided detailed information such as time, latitude, longitude, speed, and crack classification. This comprehensive system enabled users to efficiently identify and analyze the precise locations of the detected pavement distress, facilitating informed decision-making for effective road maintenance and repair initiatives.

Fig. 5.3 Mapping for Cracks

Fig. 5.4 Mapping for Potholes

Fig. 5.5 Mapping for Alligator Cracks

Fig. 5.6 Mapping for All Classifications

VI. Conclusion and Recommendations

The researchers have successfully developed a system for classifying pavement distress using the Yolov5 algorithm with PyTorch in the Python programming language. Through the implementation of image preprocessing techniques and the careful selection of a suitable dataset, the training model exhibited effective performance in streaming conditions, striking a balance between assessment speed and precision. The system's design incorporated an interfaced camera and the Jetson Nano microcomputer, which harnessed GPU capabilities and supported CUDA features, thereby facilitating efficient processing.

The study recommends several improvements for the system classifying pavement distress. Firstly, implementing a 1-kilometer documentation approach instead of individual road fault documentation would provide a comprehensive catalog scheme, enhancing organization and accessibility. Secondly, incorporating a function to measure the area of pavement distress would enable more accurate assessments of severity and impact. Additionally, enhancing the system's adaptability to diverse road types and upgrading hardware and models for improved efficiency and precision are suggested. These recommendations aim to enhance decision-making, resource allocation, and overall road network maintenance.

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