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A Low-Cost, Highly Deployable Traffic Infrastructure Monitoring Solution based on Machine Vision

-- Exploration of the Application of Innovative Monitoring Devices and Systems

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Abstract

This study presents an innovative machine vision-based solution to address the challenges of traffic infrastructure monitoring. The proposed system integrates multiple modules to create a low-cost, highly deployable monitoring device and system. It significantly enhances monitoring efficiency and accuracy, offering a new perspective for the development of traffic monitoring technologies. Traditional methods, which mainly rely on manual inspections and fixed sensor networks, suffer from issues such as high costs, limited flexibility, and low timeliness. By introducing machine vision technology and deep learning algorithms, the system enables automatic crack detection and provides a cost-effective, highly deployable monitoring solution. The study provides a new path for advancing traffic infrastructure monitoring technologies.

Keywords

Machine Vision; Traffic Infrastructure Monitoring; Low-Cost; High Deployability; Intelligent Early Warning.

1. Introduction

Traffic infrastructure is crucial to the economic development of modern societies, and its safety directly affects public safety and economic efficiency. According to statistics, the direct economic loss caused by the diseases of bridges and roads in China each year exceeds hundreds of millions of yuan [1]. Traditional monitoring methods mainly rely on manual inspections and fixed sensor networks, which suffer from several limitations:

1) High Costs: The cost of deploying high-precision sensors at a single point exceeds 10,000 RMB, limiting large-scale applications [2]

2) Poor Flexibility: Wired power supply and data transmission restrict deployment in areas such as mountainous regions and sea-crossing bridges, where coverage is less than 40% [3].

3) Low Timeliness: Manual inspections typically occur at intervals of over three months, making it difficult to detect sudden damage events in time [4].

Recent advancements in machine vision technology offer new opportunities for traffic monitoring [5]. For example, one study applied deep learning algorithms to automatically identify road surface cracks with an accuracy rate of 89% [6]. Another developed a drone-based bridge inspection system with a limited endurance of 30 minutes [7]. This study proposes a solution that optimizes hardware and algorithms, offering both low-cost and high-reliability monitoring. The key innovations include:

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1) Portability: No need for external wiring.

2) Multi-modal Sensor Dynamic Registration: Technology for aligning different sensor types in real-time.

3) Lightweight YOLOv5 Model Implementation: A compact yet efficient deep learning model for image processing.

2. System Design based on Machine Vision

2.1 System Architecture and Module Composition

The monitoring system consists of several key modules: image acquisition, image processing, data transmission, power supply, and cloud platform (Figure 1). Core parameters are detailed in Table 1.

Table 1. Core parameters are detailed

Module	Low-Configuration	High-Configuration
Image Sensor	OV5640 (5 MP)	IMX708 (12 MP)
Processor	ESP32-CAM	RK3566
Communication	4G (AIR-780E module)	4G (AIR-780E module)
Endurance	180 days	90 days

The image capture module includes a variety of camera types, providing strong support to meet different monitoring needs. For low-end configurations, cameras like the OV2640 DVP are selected. These cameras are low-cost, power-efficient, and have a resolution of up to 2 megapixels. The focal length typically ranges from 2.8mm to 4mm, and they can capture images at a rate of 5-10 frames per second, meeting the needs of large-scale monitoring. In scenarios where monitoring accuracy is not critical but broad coverage is required, such as routine road condition monitoring on urban streets, the DVP cameras can efficiently complete the task, quickly detecting general changes in road conditions.

For high-end configurations, USB cameras such as the IMX315 are used, offering a resolution of over 5 megapixels and a focal length range of 8mm-12mm. These are employed for detailed monitoring of high-value damaged or abnormal areas. When the DVP camera detects an anomaly in an area, such as a suspected road crack expanding or an abnormality in bridge structures, high-definition USB cameras like the IMX708 come into play, taking detailed photos of these regions to provide clear images for subsequent accurate disease assessment. This module is designed to be adaptable to environmental conditions, with waterproof, dustproof, and temperature-resistant features. The sealed gasket and waterproof shell ensure an IP65 protection rating, guaranteeing stable image capture in complex traffic environments, whether it be rainy city streets or highways under intense sunlight.

The image processing module uses smart hardware, selecting different devices based on needs. The ESP32-CAM, with its low cost and small size, is suitable for low-end configurations and can perform initial image processing. This includes using the JPEG compression algorithm to reduce image size while employing algorithms like bilateral filtering to optimize image quality and reduce transmission bandwidth requirements. In low-end configurations, where the amount of captured image data is relatively large, without effective processing, transmission and storage would face significant pressure. The ESP32-CAM reduces the difficulty of data processing and transmission by applying these algorithms while ensuring the integrity of the essential image data.

For high-end configurations, a Linux development board with greater processing power is used to handle more complex image tasks, such as finer noise reduction and enhancement for high-definition images. When processing high-resolution images, the Linux development board utilizes its powerful computing capabilities to eliminate noise interference and enhance image details, making the disease-related information in the images clearer for further analysis and judgment.

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The data transmission module uses 4G DTU hardware combined with the MQTT protocol to reliably and real-time transmit processed data to the cloud platform. For example, the selection of the YingErda AIR780E DTU module ensures stable network connectivity in regions with varying local area network coverage.

The power supply module is equipped with rechargeable lithium batteries, such as the 18650 lithium battery pack, with a capacity ranging from 3000mAh to 5000mAh, providing continuous power to the device. In certain scenarios, solar panels, such as the Hanergy flexible solar panels, with a power range of 5W to 10W, are added to supplement the power in outdoor environments and extend the device's endurance. Power management chips like the TP4056 are used to manage battery charging and discharging, increasing battery lifespan. In outdoor monitoring points with abundant sunlight, the solar panels can continuously charge the lithium batteries, reducing the frequency of battery replacements and lowering maintenance costs. The power management chip precisely controls the battery’s charging and discharging processes, preventing overcharging or deep discharging, thus extending the battery’s service life.

The cloud platform module is deployed on a server and connects to the internet to receive data. It has powerful data storage, processing, and analytical capabilities. The YOLOv5 algorithm is integrated for image recognition to promptly detect anomalies in traffic infrastructure. At the same time, deep learning frameworks like TensorFlow are used to extract and analyze features from the collected images, enabling disease severity assessment and trend prediction. Through the user interface, users can remotely access monitoring data and system status, as well as utilize fault diagnosis tools to monitor device operation in real time. Once the cloud platform receives image data, the YOLOv5 algorithm quickly identifies any abnormalities in the traffic infrastructure, such as road cracks or bridge structure damage. The TensorFlow framework further analyzes these anomalies, assesses the severity of the diseases, and predicts their development trends. Users can remotely view the monitoring data and system status anytime and anywhere. When a fault occurs, the fault diagnosis tool helps quickly locate the problem, facilitating timely maintenance.

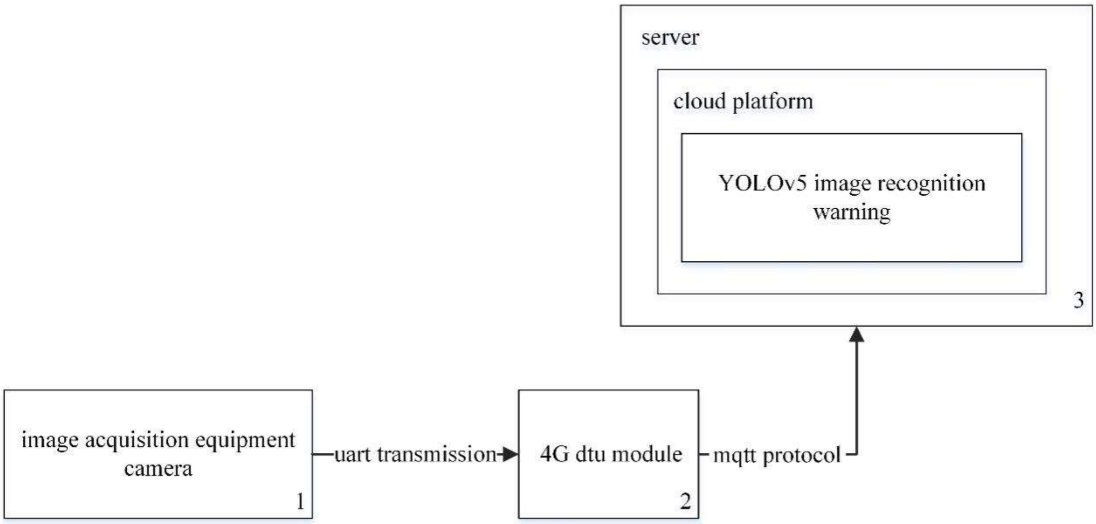

Figure 1. Schematic diagram of hardware structure of monitoring system based on machine vision

2.2 Working Principle

The system operates by periodically capturing traffic infrastructure images based on preset intervals. These images are transmitted via TTL serial port to the image processing module, which processes and compresses the data. The processed data is then transmitted through 4G networks to the cloud platform. The cloud platform uses YOLOv5 for object detection and, when anomalies such as crack expansion or foreign object intrusion are detected, triggers an alert system. This enables real-time monitoring and early warning of infrastructure issues.

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3. Advantages and Innovations of the Monitoring System

3.1 Low-Cost Design

The system adopts a strategy of combining low-cost and high-end devices to avoid over-provisioning and reduce equipment costs. By selecting the appropriate devices for different monitoring requirements, it balances performance with cost. For example, low-cost DVP cameras and ESP32-CAM devices are used for large-area monitoring, while high-end devices are deployed for detailed inspection in critical areas. The power module also optimizes energy consumption by combining solar power with rechargeable lithium batteries, reducing the cost and frequency of battery replacements. Data transmission is handled by selecting appropriate 4G DTU hardware and MQTT protocols to ensure stable transmission while controlling costs.

3.2 High Deployability

The device features a portable and completely wireless design, eliminating the need for power and network cables at the installation site, thus offering flexible installation options. It can be mounted on existing structures such as streetlights, surveillance poles, gantries, or installed using standalone poles. This flexibility allows for rapid deployment to various locations based on actual monitoring requirements. In urban roads, existing streetlight poles can be utilized for installation, saving additional costs and space; in remote areas or places without suitable mounting structures, standalone poles can be used. The camera angle can be adjusted and fixed on-site to adapt to different traffic environments. Depending on the monitoring scenario and objectives, installers can adjust the camera's angle on-site to ensure optimal monitoring images are captured. The device has a protection rating of at least IP65, with a housing made of ABS engineering plastic, providing waterproof, dustproof, and high/low-temperature resistance capabilities, ensuring stable operation in environments ranging from -30℃ to 60℃. This significantly enhances deployment flexibility and range. Whether in the cold northern winters or the hot southern summers, the device operates normally, adapting to various complex traffic environments.

3.3 Maintenance Convenience

By inputting the installation site's geographic coordinates, the device's location can be queried through a remote operation and maintenance platform, facilitating subsequent maintenance and positioning. During installation, the device acquires its geographic coordinates either via a positioning chip or manual input, storing this information internally. When maintenance or inspection is required, personnel can swiftly locate the device through the remote platform, enhancing maintenance efficiency. The device also features a power alert function to monitor battery voltage levels, enabling the platform to assess the device's power status. This function allows staff to promptly understand the device's power condition, prepare for recharging or battery replacement in advance, and prevent operational interruptions due to insufficient power, thereby ensuring continuous monitoring tasks.

3.4 Long Endurance and Intelligent Monitoring

The power module's combination of a solar panel and lithium battery ensures the device's long operational endurance, reducing the hassle and cost of frequent battery replacements. The intelligent detection and analysis functionality on the cloud platform uses advanced algorithms to deeply mine the acquired image data, not only enabling timely detection of anomalies but also evaluating the extent of damage and predicting development trends, thereby providing a scientific basis for the maintenance and management of infrastructure.

4. Application Scenarios and Implementation Cases

4.1 Pavement Monitoring

In the pavement monitoring scenario, the installation height of the device is determined by the installation method (either self-supported poles or utilizing existing road infrastructure). To ensure both maintenance accessibility and theft prevention, an installation height of 5-7 meters is ideal. For

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example, on a two-way, three-lane road, a single camera can effectively cover the 20-meter width of the road and extend 40 meters along the driving direction. The vertical lens has a viewing angle of approximately 60 degrees. Typically, the spacing between city streetlights ranges from 25 to 50 meters, which suits the installation needs.

The system works by continuously and automatically capturing pavement images at preset intervals. The cloud platform then utilizes the YOLOv5 algorithm to identify surface cracks, potholes, and other forms of damage. When such issues are detected, timely alerts are generated to aid in road maintenance decisions. Additionally, to meet varying monitoring needs, cameras with different focal lengths can be swapped in and out to acquire more accurate images, ensuring a high degree of monitoring precision.

4.2 Bridge Monitoring

For concrete structure bridges, such as elevated bridges, reinforced concrete beam bridges, and arch bridges, the monitoring system covers a wide array of potential damage types, including road surface defects, railing and lighting damage, as well as issues with the bridge supports.

1) Bridge Road Surface Monitoring: This includes monitoring for surface damage, railing issues, and street lighting problems.

2) Bridge Side Monitoring: Monitoring the side surfaces of the bridge for peeling, exposed steel reinforcement, cracks, and similar damage.

3) Support Monitoring: Includes the assessment of support-related issues, such as settlement, deformation, and displacement.

Two primary installation methods are used:

- Bridge Body Installation: Provides high-quality, detailed images that capture minute damages.
- External Installation: Offers a wider field of view, enabling the monitoring of overall bridge shape changes.

A single camera can monitor damage within a 40-meter range. For large-scale damage monitoring, a comprehensive coverage can be achieved by setting up multiple camera points at regular intervals. The system can monitor up to 100 meters of bridge structure at once, and in the case of large-scale objects, the camera array can be deployed continuously along the structure.

The installation methods are specifically tailored for different monitoring goals:

- Method 1 (Bridge Support Monitoring): This installation focuses on capturing the entire support structure, particularly for observing changes in support shape and displacement over time.
- Method 2 (Targeted Support Points Monitoring): This method targets key areas such as connection points and expansion joints, where damage is more likely to occur.

During the monitoring process, the cooperation between different installation positions and camera angles allows for comprehensive and accurate assessments of the bridge's health. Once anomalies are detected, the system triggers an early warning, providing essential data for maintenance and repairs, and ensuring the safety and continued operation of the bridge.

5. Application Scenarios and Implementation Cases

5.1 Bridge Inspection Photo Collection and Accumulation

For road surface monitoring, the device is installed at an optimal height (5-7 meters), depending on the installation method (independent poles or existing infrastructure). The camera can cover a 20-meter-wide road with a 40-meter detection range. By regularly capturing images, the system uses YOLOv5 to detect pavement cracks and potholes, providing timely alerts for road maintenance.

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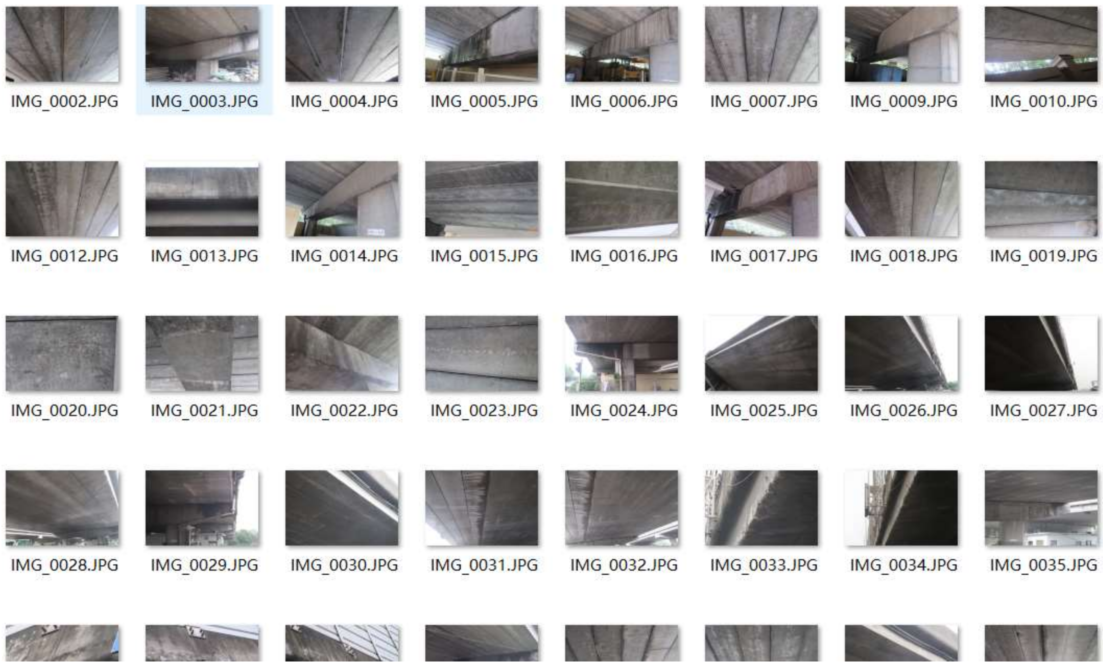

Figure 2. Bridge Inspection Images

5.2 Deep Learning-Based Image Recognition Algorithm

Due to insufficient foundational data, the first version of the image recognition system was incomplete, mainly using simple image processing algorithms and traditional machine learning models. However, thanks to the large accumulation of data since 2018, there is now an opportunity to develop a more refined image recognition model.

The new system adopts a deep learning model, which significantly improves image recognition accuracy and efficiency. This system uses a classic deep learning model, implementing end-to-end object detection with a standalone CNN model. The system workflow is as follows: the input image size is first adjusted to 448x448, then passed through the CNN network, and finally, the network's prediction results identify the target. Compared to the R-CNN algorithm, this is a unified framework that operates faster.

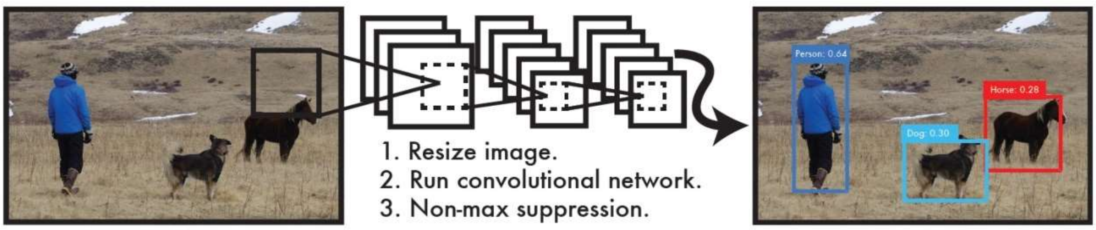

Figure 3. Deep Learning Model

The deep learning network model is as follows. A convolutional network is used to extract features, followed by a fully connected layer to generate predictions. The network structure is based on the GoogleNet model, containing 24 convolutional layers and 2 fully connected layers, as shown in the figure below. For the convolutional layers, 1x1 convolutions are primarily used, followed by 3x3 convolutions. Leaky ReLU activation functions are applied to the convolutional and fully connected layers, with the final layer using a linear activation function.

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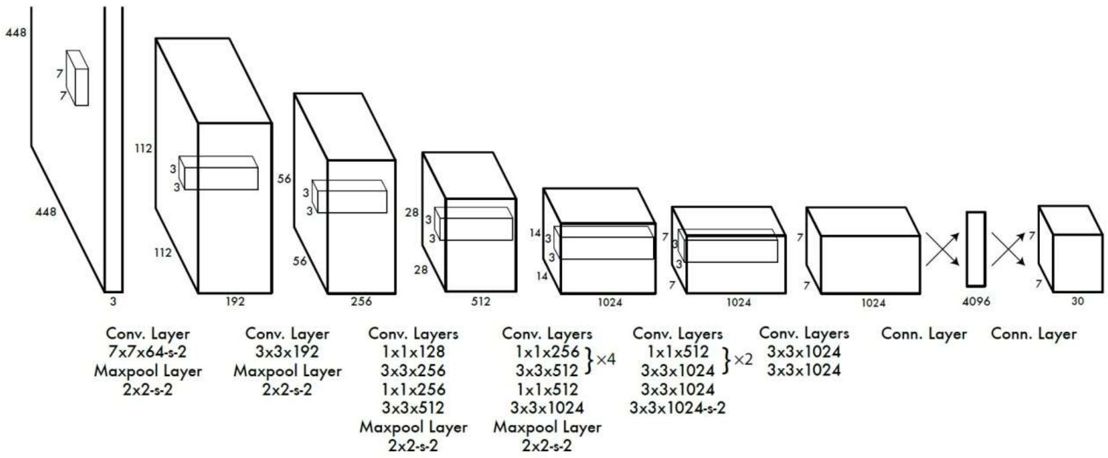

Figure 4. Deep Network Structure

5.3 Data Labeling, Modeling, and Training

The bridge damage images collected in section 4.1 were manually labeled in preparation for training the deep learning model. Based on the current data set (a total of 706 images) and the types of damage included, the main categories for manual labeling were: pavement damage, bottom plate damage, hinge joint damage, and cap beam damage.

Once the image labeling was completed, model training could begin. The network training for this project was performed on Linux, with GPU acceleration. After 1,000 iterations, the test results showed satisfactory accuracy in detecting damage, making it ready for future practical use.

5.4 Practice

The system was used to inspect a bridge on Shanghai's Outer Ring Expressway S20, and the damage ratio is shown in the figure below.

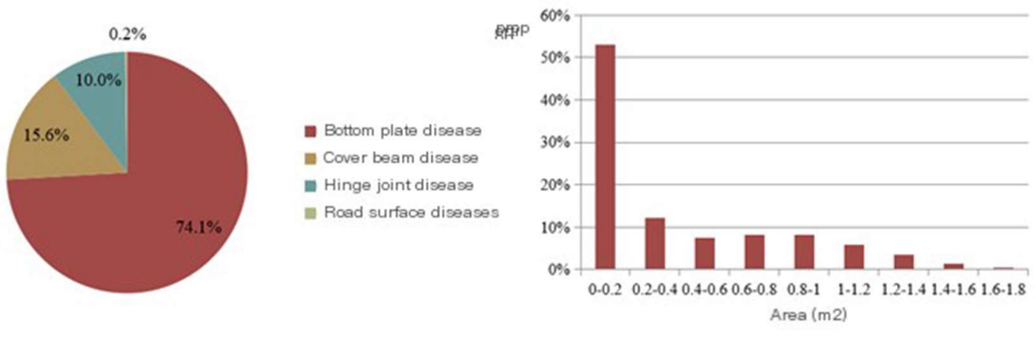

Figure 5. Bridge Inspection Results

6. Conclusion

This study proposes a low-cost and highly deployable traffic infrastructure monitoring solution based on machine vision, effectively addressing the limitations of traditional monitoring equipment. Through innovative modular design, coordination between low- and high-end devices, and flexible deployment, the system achieves efficient monitoring. In practical applications, the solution has shown excellent performance in road and bridge monitoring, enabling timely detection of damage and providing valuable support for infrastructure maintenance. Future improvements will focus on optimizing module performance, expanding monitoring capabilities, and integrating more advanced image recognition algorithms, enhancing monitoring precision and intelligence. As technology

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evolves and new application scenarios emerge, this solution holds great potential for wider deployment in the field of traffic infrastructure monitoring.

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