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Design and Development of a Real-Time Monitoring System for Highway Road Surface Anomalies

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Abstract

The recent unprecedented increase in highway networks in India has increased the need to maintain safe and smooth roads. The increasing number of road surface anomalies such as cracks, surface irregularities, and anomalies can lead to vehicle damage and accidents. This research work presents the design and development of a real-time monitoring system for detecting anomalies in highway road surfaces. The proposed system utilizes the machine vision model integrated with cameras, sensors, and edge computing to provide timely and accurate alerts for the drivers and also to the road maintenance authorities. The proposed solution is designed specially to work under different environmental conditions and enable large-scale deployment. The output generated from the proposed model is visual feedback of the detected anomalies and its severity analysis, enabling quick road maintenance actions.

Keywords: Image Processing, Crack Detection, Neural Networks, Surface Anomalies, Sensors, Edge Computing.

1. Introduction

Highways are an essential transport infrastructure. They form a backbone for goods and people movements that enable economic activities and connections between communities. While demand grows in terms of more efficient and reliable transport, the need

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to maintain safe and smooth highways assumes even greater importance. On the other hand, the road surface anomalies such as potholes, cracks, and uneven surfaces continue to pose a challenge. Apart from causing critical dangers and even accidents to the vehicles as well as their passengers, they also increase the total maintenance cost of the vehicle, increased fuel consumption, and delays in traveling time [1].

The conventional traditional road maintenance strategies rely mostly on manual inspections, which are labour-intensive and time-consuming. Secondly, it will also suffer from human error. Introducing periodic checks may often result in delayed identification of critical conditions, thereby increasing the occurrences of accidents or extensive destruction to the road's infrastructure. All these limitations highlight the need for more proactive, accurate, and timely solutions. In recent years, smart technologies have opened up new possibilities. By integrating machine learning, sensors, and real-time data analysis, the road maintenance practice can be easily transformed. Automation of highway monitoring systems has now made it possible to sense anomalies on road surfaces, thereby making it possible to enable quicker response and prevention [2].

This research study proposes an idea of a highway road surface anomaly detection and evaluation system in real-time based on a combination of sensors and machine vision technology. Cameras, GPS, accelerometers, collect data over the surface of the road, and further processing through algorithms of machine learning will identify a variety of defects in roads with reasonable accuracy. These technologies integrated provide comprehensive monitoring to authorities over highways with data-driven and scalable solutions for proactive maintenance and repair. This will enable the public works department to optimize their operational efficiencies as they reduce costs concerning maintenance while most importantly improving the road safety for all users.

2. Literature Review

This research study reviews various approaches for real-time detection of anomalies in roads using several technologies and methodologies. A number of research studies advance new systems employing mobile edge computing, IoT frameworks, and machine learning algorithms to improve the monitoring of road conditions. For example, Zheng et al. [3]

developed a QF-COTE technique for real-time anomaly detection but outperforms other existing methods regarding both accuracy and speed. Abdelraheem et al. [4] employed an IoT framework utilizing accelerometers, and Gabbar et al. [5] developed a HAIS system for inspecting highway conditions. Zhao et al. [6] as well as Gagliardi et al. [7] analyzed the application of different sensor technologies, such as fiber optic sensing and acoustic data, to detect surface anomalies. Smartphone-based systems [8, 9] are low-cost solutions achieved by machine learning and sensor data and obtained high accuracy in detecting road defects. For example, in the studies like [10] there is a limitation of requiring real-time systems, larger datasets, or scalability improvements, creating areas that need to be addressed in future research.

The employment of multiple sensors, such as accelerometers, vibration sensors, and cameras, is widespread in road anomaly monitoring, coupled with the techniques of machine learning. For instance, in [11] the authors suggest combining sensors with the best optimized DNN models on resource-constrained devices, which reflects some progress in cheaply monitoring road health. One area that dominates the study is machine learning, in particular deep learning, about sensor data analysis for real-time detection of defects. A prominent example of such a study is [12], which applies deep learning to detect defects with limited training data, thus being more efficient for real-world applications. Many studies express the limitations of scaling these technologies for large-scale deployment. For example, [13] identifies shortcomings in the detection of negative road anomalies and limitations in existing sensor technologies. Another significant emphasis is real-time data processing, like in [14], which makes use of vibration analysis and the creation of real-time maps of potholes, thereby improving both detection as well as cost efficiency compared to traditional methods. Several works focus on integrating IoT technologies into smart road infrastructures. [15] is one of the proposed system using IoT for real-time monitoring of pavement conditions; it highlights problems concerning sensor durability and data redundancy, which affect long-term viability.

Despite the progress, many studies highlight the need for more robust, scalable solutions, addressing limitations like the computational costs, sensor durability, and environmental interference. This research makes progress towards improving the accuracy of detection and optimizing machine learning algorithms for large-scale deployments.

3. Proposed Methodology

The proposed methodology begins with data collection, whereby high-resolution cameras installed on moving vehicles capture video footage of road surfaces, and GPS modules provide real-time geolocation data that can be transferred to Google Cloud Storage for centralized storage. Each time data is uploaded, Google Cloud Functions gets automatically triggered to extract frames from such video footages that are relevant. Only useful data is thus processed. The AI Platform then feeds these frames through a pre-trained Convolutional Neural Network (CNN), designed to identify road anomalies such as potholes and cracks.

3.1 Proposed CNN Model

The proposed CNN model is trained using the images collected from the Annotated Potholes Image Dataset from Kaggle (https://www.kaggle.com/datasets/chitholian/annotated-potholes-dataset). The model outputs confidence intervals and severity scores for each anomaly.

The CNN model for pothole detection and severity prediction takes in road surface images and outputs both the location (bounding box) and the score of detected potholes. In its architecture, it includes a series of convolutional layers with max-pooling layers for feature extraction. The last layer is the output layer, which produces five values: four for the box coordinates (x, y, width, and height) and the last one for the severity score that signifies the level of damage or pothole size. The dataset on which the model is trained contains road surface images, with bounding box annotations, as well as associated severity scores. The loss function used is Mean Squared Error, applied commonly for regression tasks, which enables the model to learn how to closely predict both the bounding box and the score of severity.

Algorithm: Pothole Detection Using Convolutional Neural Network (CNN)

Step 1: Define the CNN Model

1. ***Initialize the Sequential Model.***
   Input: Image of shape (224, 224, 3).
2. ***Convolutional and Pooling Layers***

- *Convolutional layer with 32 filters, a 3x3 kernel, ReLU activation, and input shape (224, 224, 3).*
- *Max-pooling layer with pool size (2, 2) to reduce the spatial dimensions.*
- *Another convolutional layer with 64 filters, a 3x3 kernel, and ReLU activation.*
- *Max-pooling layer with pool size (2, 2).*
- *Convolutional layer with 128 filters, a 3x3 kernel, and ReLU activation.*
- *Max-pooling layer with pool size (2, 2).*
- *Another convolutional layer with 128 filters, a 3x3 kernel, and ReLU activation.*
- *Max-pooling layer with pool size (2, 2).*

3. ***Flattened Layers***

   Conversion of multi-dimensional feature maps into a 1D vector.

4. ***Output Layer***

Fully connected (dense) layer with 5 units (4 for bounding box coordinates: x, y, width, height, and 1 for severity score).

A sigmoid activation function to get normalized values between 0 and 1.

Step 2: Compile the Model

Optimizer

Adam optimizer (optimizer='adam').

Loss Function

Mean squared error (mean_squared_error) as the loss function for regression tasks.

Evaluation Metric

accuracy as an evaluation metric during training.

Step 3: Training Data

Image Data:

Load or generate training images.

Assume train_images has the shape (num_samples, 224, 224, 3), representing RGB images.

Label Data

Prepare training labels with bounding box coordinates and severity score.

Assume train_labels has the shape (num_samples, 5), representing 4 bounding box values and 1 severity score.

Step 4: Model Training

Model Fitting

Train the model using model.fit() with the following parameters:

- *train_images: Input images.*
- *train_labels: Ground truth bounding box and severity.*
- *epochs: Number of training iterations.*
- *batch_size: Number of samples processed before the model is updated.*

Step 5: Save the Model

Save the Trained Model

model.save('pothole_detection_model.h5') to save the trained model for future use.

Step 6: Inference on New Image

Load the New Image:

Read the image from file using OpenCV (cv2.imread()).

Resize the image to (224, 224).

Normalize the Image:

Scale the image pixel values between 0 and 1 by dividing by 255.

Make Predictions:

Pre-processed image to the trained model for prediction.

The model will output 5 values:

- *(x, y, width, height) for bounding box coordinates.*
- *severity for the pothole severity score.*

Scale Predictions:

Scale the bounding box coordinates (x, y, width, height) to the original image size.

Multiply x, width by the original image width and y, height by the original image height.

Draw Bounding Box:

Draw a rectangle on the image using the predicted bounding box coordinates with OpenCV's cv2.rectangle() function.

Display Results:

Use OpenCV or Matplotlib to display the image with the drawn bounding box and severity score.

Step 7: Model Testing with Real Images

detect_potholes() Function:

Pass the path of the test image and the trained model to the function.

The function will display the image with the detected pothole bounding box and severity score.

Once the model is trained, it can be deployed on edge devices or cloud platforms to analyze new images. During inference, the model processes an input image by resizing it to fit the input shape, normalizing the image, and predicting the bounding box and severity score. The bounding box is then drawn on the original image using OpenCV, along with the severity score, which is displayed as text.

3.2 Proposed User Interface

The results, including the detected anomalies and corresponding GPS coordinates, are stored in BigQuery, allowing for efficient querying and analytics. A user-facing web application, hosted on Google App Engine, provides a real-time dashboard where anomalies are visualized on a map. Users can review detailed reports, including images, severity scores, and location data. Alerts are sent to relevant authorities or maintenance crews via email or SMS when significant issues are detected, ensuring timely intervention. For added accuracy, the Public Works Department (PWD) can manually review the flagged anomalies, verifying their validity and updating the PWD Information System.

The detailed workflow of the proposed methodology is shown in Figure 1.

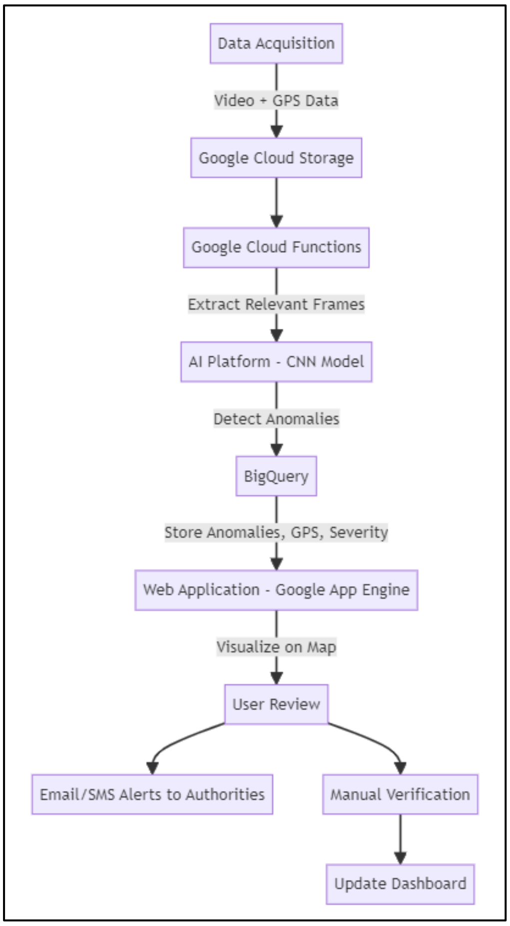

Figure 1. Proposed Workflow Real-Time Monitoring System for Road Surface Anomalies

4. Results and Discussion

Implementation of the pothole detection system with high-resolution cameras, GPS modules, and machine learning techniques achieved a promising outcome with an accuracy rate that remains around 90 percent in detecting road anomalies. A CNN minimized false positives and produced confidence scores between 0.55 and 0.98 for detected potholes and represented reliable assessments of road conditions, the obtained results for an input image is shown in Figures 2 and 3.

Figure 2. Input Image

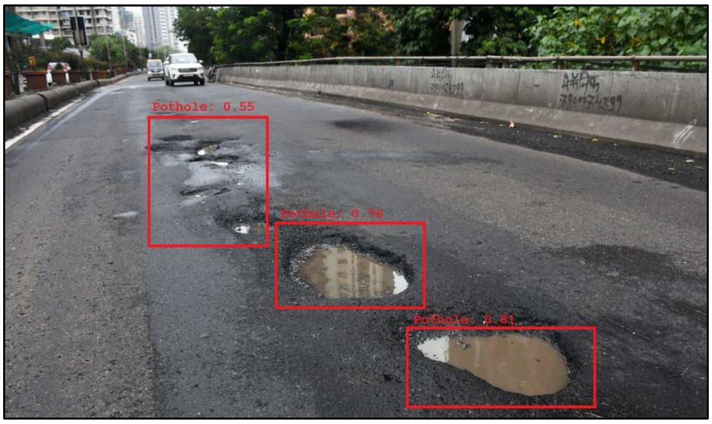

Figure 3. Pothole Detected Output

The integration of GPS data with detection results as shown in Table 1 enabled precise mapping of pothole locations, enabling targeted maintenance efforts by the Public Works Department (PWD).

Table 1. GPS Coordinates with Detection Results

GPS Coordinates

Confidence Intervals	Damaged Area	Latitude	Longitude	Run date
[0.96021457]	450	19.075984	72.877656	01/09/2024
[0.97561234]	320	28.613939	77.209021	04/09/2024
[0.95078912]	200	13.082681	80.270718	04/09/2024
[0.98947345]	510	22.572646	88.363894	06/09/2024
[0.94013456]	380	12.971599	77.594566	07/09/2024
[0.96541235]	250	19.218331	84.503718	10/09/2024
[0.92578345]	150	26.912434	75.78727	11/09/2024
[0.97082934]	275	17.385044	78.486671	14/09/2024

Additionally, the system's edge computing capabilities allowed for real-time processing of video feeds, significantly reducing the time from data capture to anomaly detection. The user-friendly web application efficiently displayed detected anomalies on an interactive map and allowed access to detailed reports, featuring images and severity scores as well as the GPS coordinates associated with them as shown in Figure 4.

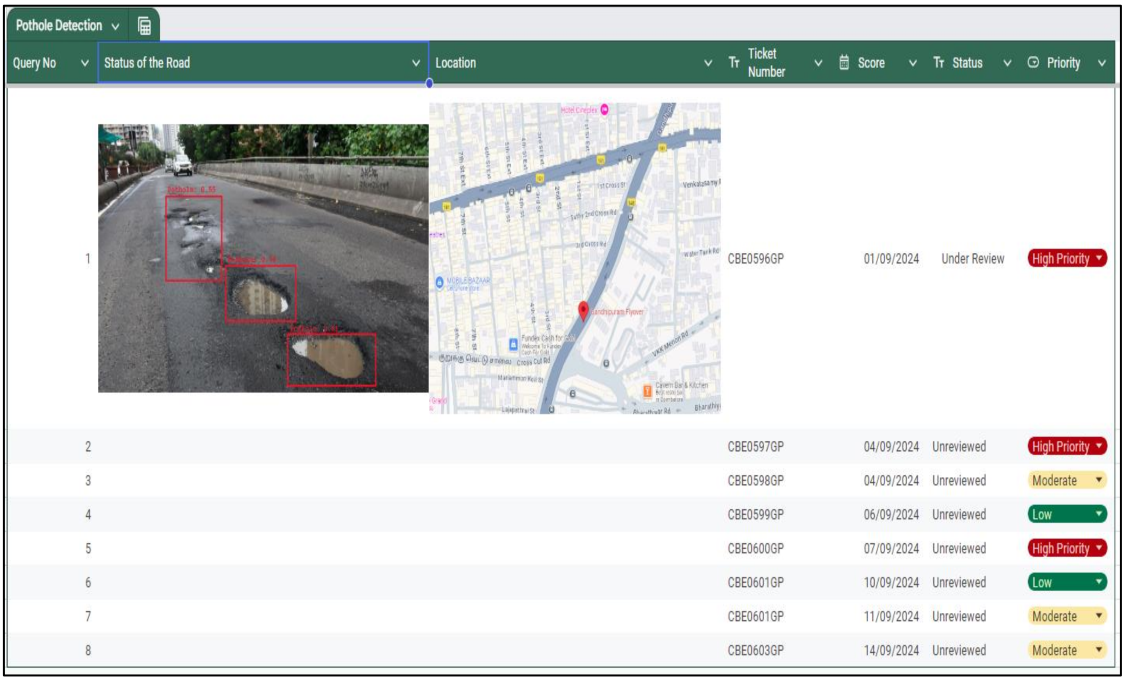

Figure 4. Developed Interactive Dashboard

5. Conclusion

This research work successfully demonstrates the effectiveness of a sophisticated pothole detection system, integrating high-resolution cameras, GPS modules, and advanced machine learning algorithms. The fact that it can identify road anomalies with close to 90% accuracy gives an impressive lead over traditional road maintenance practices, where municipalities can promptly address such safety concerns due to poor road conditions. Using the real-time data processing and visualization tools will provide critical insights to urban planners and maintenance teams for effective on-time interventions and resource allocation. Although the system demonstrates very prominent advancements in road maintenance technology, misclassifications may periodically result from variability in road surfaces and sometimes environmental factors. Future updates would include improving the CNN model using diverse datasets, integrating various sensors, and exploring more advanced machine learning techniques for increasing detection rates.

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