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STUDYING THE USE OF LOW-COST SENSING DEVICES TO REPORT ROADWAY PAVEMENT CONDITIONS

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16. Abstract

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ABSTRACT

This report investigates the application of low-cost sensing technologies, including GPS, accelerometers, and smartphones, to monitor roadway pavement conditions in real time. By leveraging widely available sensors embedded in vehicles, this research demonstrates how machine learning models can detect and classify road anomalies, such as cracks and potholes, significantly improving road safety and reducing operational costs. The study also presents a mixed integer linear programming (MILP) model to optimize maintenance and repair (M&R) activities under budget constraints. These models help transportation agencies prioritize road repairs, ensure efficient resource allocation, and minimize traffic disruptions. By adopting low-cost sensor-based approaches, municipalities can move toward more proactive, data-driven maintenance strategies, ultimately improving road network longevity and user satisfaction.

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1. INTRODUCTION

Road surface irregularities, such as cracks, joints, and potholes, have a significant impact on ride quality, safety, travel time, traffic conditions, and driving costs. The Intentional Roughness Index (IRI) is used as the primary quantifiable indicator of road surface condition. It calculates the total vertical displacement of vehicles passing over a road, divided by the traveled distance, and is expressed in units of meters per kilometer or inches per mile. Therefore, IRI quantifies the effect of road surface irregularities on the road profile, which affects driver safety and increases driving costs, including fuel consumption, repair and maintenance, depreciation, and tire costs. A lower IRI value indicates a flatter road surface profile, resulting in less disruption to traffic flow and improved travel time, cost, and safety for road users. Additionally, it reduces the maintenance and repair costs of the road surface. For instance, an IRI of 0 inch/mile represents a perfectly flat profile. While there is no upper limit for IRI, in practice, IRI values above 500 inches/mile indicate pavements that are nearly impassable for vehicles except at reduced speeds (Park et al., 2007). It is estimated that a 64 inches/mile increase in IRI results in a 2.5% increase in fuel consumption and a 1% increase in tire wear, respectively.

Several techniques can be used to inspect the roadways performance and identify issues, like cracks, potholes, and other forms of distress. These techniques include visual assessment by inspectors, the use of specialized vehicles equipped with laser devices and cameras to measure distress, and the involvement of citizens who report their observations. However, these techniques suffer from inefficiency, high labor requirements, and significant costs. For instance, it is estimated that on average, these inspection techniques cost $429 per mile (Croze & Zilay, 2014). More advanced techniques, such as image processing and video analysis, have also been evaluated (Sharma et al., 2020; Zakeri et al., 2017). However, these techniques heavily rely on the quality of images and videos, which limits their applicability to daylight and favorable weather conditions. Moreover, implementing these techniques necessitates significant data storage capacity, approximately 1.6 GB per mile, and the computational analysis of such large datasets is computationally demanding (Yan & Yuan, 2018). As a result, transportation authorities and municipalities are continuously seeking low-cost and efficient pavement evaluation technologies, along with a centralized information system that provides real-time road status updates (Jahanshahi et al., 2013). Furthermore, maintaining an up-to-date database of road surface conditions using the aforementioned techniques is highly challenging, if not impossible (Chang et al., 2005; S.-E. Chen et al., 2011). Additionally, these techniques rely on multiple data collection devices, such as video/image recorders, GPS sensors, and motion sensors, all of which require calibration and synchronization. For instance, if the GPS signal is lost or the batteries of the video/image recorders are discharged, the data collected from other devices becomes useless. Finally, the widespread implementation of the discussed techniques is hindered by the requirement for technical expertise and the labor-intensive nature of the operations involved.

In addition to inspecting and quantifying road surface quality, transportation agencies must utilize these metrics to strategically allocate funds to decelerate deterioration rates, maintain, and improve road surface conditions over time. The optimization of road surface repair and maintenance activities combined with thoughtful budget allocation is critical. However, agencies face challenges prioritizing maintenance activities across road networks under tight budgets. Optimization models facilitate planning and scheduling of maintenance activities to improve road surface conditions over time considering budgetary constraints. Studies demonstrate linear programming, integer programming, and multi-objective optimization efficiently allocate resources and mitigate deterioration (Chan et al., 2003; W. Chen & Zheng, 2021; de la Garza et al., 2011; Torres-Machi et al., 2017; Torres-Machí et al., 2014). These quantitative methods empower agencies to boost pavement condition and longevity network-wide while being fiscally responsible.

An efficient solution to address the limitations discussed above is to use low-cost widely accessible sensors, such as GPS, accelerometer, and cellphones, to automate inspection of roadway pavement conditions (Koch et al., 2015; Spencer Jr et al., 2019). There is a pressing need for innovative solutions to reduce operational costs and time, enhance data collection simplicity, facilitate maps of roadway pavement conditions, and maintain up-to-date conditions of existing transportation networks. Finally, there is a need for new optimization models that can prioritize and identify the optimal selection of maintenance and repair treatments for road networks while considering budgetary limits. These new models provide valuable insights into creating action plans that allocate sufficient funds to slow down the degradation of road conditions and strive for improving the existing road conditions.

2. RESEARCH BACKGROUND

The present work focuses on two areas of ongoing research (1) road surface quality monitoring; and (2) road repair and maintenance planning, which are discussed in the following sections in more details.

2.1 Road Surface Quality Monitoring

In most developing countries, road networks are poorly maintained due to lack of funds and technology. Therefore, the road surface monitoring system and maintenance planning mostly rely on inexpensive solutions that can be used to monitor and report road conditions using the existing vehicles on roads.

To this end, De Zoysa et al. proposed a sensor network of public transport system, BusNet, originally designed for monitoring environmental pollution. By equipping buses with various sensors and onboard GPS loggers, the system collected data of road networks. To transmit the collected data, buses visited substations where data was then transferred to a central server. By analyzing changes in acceleration and vehicle speed, BusNet successfully identified the locations of potholes (De Zoysa et al., 2007). However, a notable drawback of BusNet was its limited performance in traffic scenarios, as changes in acceleration could be caused not only by potholes but also by traffic congestion. In another study, Eriksson et al. developed Pathole Patrol (P2), a mobile sensing application deployed in taxis. The system utilized a range of sensors placed inside the taxi cabinet to record acceleration. By employing a predefined and manually labeled set of road conditions, the system accurately identified poor road surfaces. The experiment involved integrating specific hardware components, including an embedded computer, WIFI card, external GPS, and a 3-axis accelerometer. Evaluation of the system on thousands of kilometers of taxi drives in Boston demonstrated a successful detection rate of 90% for potholes (Eriksson et al., 2008). In another study, Tai et al. used smartphones accelerometer and GPS to collect motion-sensing data using a motorcycle with speed limited to a maximum of 40 km/h. Data were preprocessed by the device and sent to a centralized server for classification. Two classification procedures were performed — one to detect the road anomalies and the other to rate the road pavement quality from a predefined model of a smooth road. The motorcycle rider manually labeled the road conditions using a microphone. The developed system could achieve an accuracy of 78.5% in detecting different road surface conditions (Tai et al., 2010).

Several studies focused on developing road surface monitoring systems using standalone accelerometers and accelerometers that come with smartphones to detect speed bumps and anomalies. For example, Das et al. focused on the use of mobile devices for detection of road bumps called Platform for Remote Sensing using Smartphones (PRISM). The developed system used a three-axial accelerometer and GPS receiver to capture motion-related data when vehicles encountered road bumps. The recorded accelerometer data were locally processed in real time on the device to identify the location of the bumps before being transmitted to a central server. To ensure user privacy and prevent information misuse, they implemented a mechanism called "forced amnesia," which involved periodically stopping and restarted the application. Results demonstrated a bump detection rate of approximately 70% without forced amnesia and about 45% with forced amnesia (Das et al., 2010). In another study, Bhoraskar et al. developed a road and traffic state monitoring system capable of recording braking events, collecting information on traffic congestion, and identifying speed bumps based on vertical acceleration peaks. Their approach utilized a K-means algorithm to classify road sections as either bumpy or smooth based on the standard deviation of vertical acceleration. Results indicated the standard deviation of vertical acceleration played a crucial role in accurately localizing speed bumps (Bhoraskar et al., 2012). Similarly, Mednis et al. and Strazdins et al. focused on utilizing Android smartphones with accelerometers to identify the location of potholes (Mednis et al., 2011; Strazdins et al., 2011). Their developed systems employed various algorithms to detect changes in acceleration vibrations and determine the presence of potholes. In another similar study, Sense developed a road anomly identification system using many sensing devices from mobile phone such as accelerometer, microphone, GSM radio, and GPS (Sense, 2008).

Most of the studies discussed above focused on identifying the locations of anomalies to plan for their repairment and maintenance. However, several other studies focused on estimating the road surface or pavement condition in terms of roughness. Two popular methods to classify the road roughness are the International Roughness Index (Sayers, 1986) and the International Standards Organization (ISO) classification (Standardization et al., 1995). Road roughness is defined by American Society of Testing and Materials (ASTM) as: The deviations of a pavement surface from a true planar surface with characteristic dimensions that affect vehicle dynamics, ride quality, dynamic loads, and drainage, for example, longitudinal profile, transverse profile, and cross slope (ASTM International, 2012). Gonzalez et al. used an accelerometer to fit in a simulation car to assess road surface condition by measuring and quantifying road roughness according to ISO definition. Their simulations' results showed the roughness of road can be estimated from acceleration data obtained from the sensor (González et al., 2008). In another study, Douangphachanh and Oneyama developed a system of road surface monitoring using smartphones motion-sensing sensors. The developed system was designed based on a simple algorithm that uses several if-conditions to detect changes in recorded accelerations due to potholes and speed bumps. Additionally, the developed model was designed to be capable of estimating the road roughness based on the International Roughness Index (IRI). Based on the results from testing their developed model, it was shown there is a strong linear relationship between the IRI and magnitude of acceleration vibrations (Douangphachanh & Oneyama, 2013).

Although, most studies in the literature focused on the use of accelerometer sensing as the main indicator for road anomalies, it might not be a sufficient indicator, especially when there is a sudden stop or change in motion acceleration. To this end, several other studies focused on the use of other motion-sensing data, such as gyroscope around gravity rotation to improve the accuracy of pothole detection. For example, Mohamed et al. proposed a road condition monitoring framework that detects road anomalies, such as speed bumps, based on sensors built in Smartphones. In addition to the accelerometer, data from gyroscope around gravity rotation was utilized as a cross-validation method to confirm the detection results based on accelerometer data (Mohamed et al., 2015). In another similar study, Douangphachanh & Oneyama extended their previously road surface roughness analysis model using data from accelerometers and gyroscopes on smartphones. They identified there is a linear relationship between the road roughness and the magnitudes of vibration calculated from each axis of the accelerometers and gyroscopes. They demonstrated that the use of gyroscope data can significantly improve the accuracy of their previously models (Douangphachanh & Oneyama, 2014).

Studies discussed above, used sensing technology devices mounted on vehicles to record and collect data such as acceleration, and gyroscope. However, vehicles are equipped with suspension and dampers to attenuate certain vibrations caused by road anomalies. When the vehicle drives slowly, the wheel revolutions per minute (RPM) is low, resulting in less vibration input from the road. Increasing the speed, the wheel RPM and the frequency of the road input also increases. Accordingly, several studies focused on developing models independent from vehicle speed. For example, Seraj et al. developed a road surface monitoring system, RoADS, that used smartphones sensors, including accelerometer and gyroscope. They used a method to reduce the effects of speed, slopes, and drifts from sensor signals. The developed system used an audiovisual data labeling where the labeler used microphone and camera of the phone to manually identify different types of road conditions, such as potholes, speed bumps, road and bridge joints, and railroad crossings. The system was developed based on wavelet decomposition analysis for signal processing of acceleration and gyroscope data, and Support Vector Machine (SVM) for anomaly detection and classification. The system could identify real-time road conditions at an accuracy of nearly 90%, regardless of vehicle type, and road location (Seraj et al., 2015). In another similar study, Perttunen et al. proposed a method of linear regression to remove the linear dependency of the speed from the feature vector. They used a Nokia N95 mounted on the windshield, with accelerometer sampling at 38Hz and GPS to collect the data. Their developed system classified different road surface anomalies into two classes: mild and severe. Although their developed system did not lead into a highly satisfactory accuracy, the obtained results showed that the use of methods to remove the reliance of detection models on vehicle speed improves the accuracy of the models (Perttunen et al., 2011).

2.2 Road Repair and Maintenance Planning

Accurately anticipating pavement maintenance and rehabilitation needs and efficiently allocating road maintenance funds is essential for ensuring the longevity and quality of road infrastructure. It enables proactive planning, timely repairs, and effective utilization of resources, ultimately contributing to safer and more reliable road networks (Lu, 2011). The objective is to maintain pavements in good condition rather than waiting for major pavement failures before initiating reconstruction (Miah et al., 2020). Making early investments to uphold the integrity of roads will yield long-term benefits. Each dollar spent on maintaining roads in fair condition will save approximately \$4–\$5 that would otherwise be required to rehabilitate or reconstruct a road that has severely deteriorated (Onyango et al., 2018). Abaza & Ashur developed a non-linear stochastic optimization model for the selection of an optimum maintenance and rehabilitation treatment, with the main objective of optimizing pavement condition under constrained budgets. The model used a discrete-time Markovian model with the objective of maximizing the proportion of roads in “good” condition (Abaza & Ashur, 1999). However, the optimization model used penalty functions to avoid infeasibility and an iterative solution technique that does not guarantee optimal treatment decisions.

Optimization models, such as linear programming (LP) and mixed-integer linear programming (MILP), have become prevalent for pavement management decision-making. LP models optimize objectives and constraints represented as linear functions, while MILP includes integer decision variables. Sun et al. developed an LP model to minimize user costs and maximize pavement condition over a planning horizon. Although LP is efficient, it cannot provide project-specific solutions (Sun et al., 2020). To address this, Liu et al. formulated a MILP model that determined optimal M&R activities for individual pavement sections (Liu et al., 2022). However, computational complexity limited its network size. Building on this, Donev & Hoffmann proposed a MILP model using a rolling-horizon approach, reducing problem scale (Donev & Hoffmann, 2020). While minimizing costs, their model neglected network condition. Incorporating multiple objectives, Rahman et al. presented a MILP model to optimize agency costs, user costs, and condition (Rahman et al., 2017). But their case study was limited to a small network. To handle larger networks, Fani et al. designed a MILP model with clustering techniques that aggregated similar pavement sections (Fani et al., 2022). The technique improved scalability of MILP models, at the cost of losing location-wise accuracy of road surface improvement projects. While LP and MILP models have progressed substantially in recent years, tradeoffs remain between precision, problem size, and incorporating realistic constraints and objectives. Although linear and mixed-integer linear programming models have become prevalent, most formulations exhibit limitations in accurately representing real-world pavement deterioration and maintenance dynamics. A key shortcoming is the use of oversimplified linear deterioration rates, when, in reality, pavement condition worsens nonlinearly over time. As surfaces age and traffic volumes accumulate, deterioration accelerates geometrically rather than remaining constant. Another limitation of current optimization models is the predominant reliance on metaheuristic solution techniques, like genetic algorithms. While metaheuristics efficiently handle large problem sizes, they sacrifice optimality guarantees. These stochastic search methods only identify feasible near-optimal solutions, not proven optimal ones. Additionally, there is no definitive way to quantify the deviation from true optimality. This is concerning for infrastructure agencies making significant long-term budget decisions, where even small condition improvements could yield large user benefit-cost ratios. Yet without optimal benchmarks, the performance of metaheuristics remains theoretically unvalidated. Some studies have proposed exact solution methods, like branch-and-bound, to find guaranteed optimal maintenance plans (Fwa et al., 1996). However, such techniques still struggle with real-world problem scales and non-linearities.

3. OBJECTIVES

The objectives of the present research project are to (1) develop machine learning models using low-cost and widely accessible GPS, gyroscopes, and an accelerometer to automate the assessment of roadway pavement conditions; and (2) develop MILP optimization models for prioritizing and identifying the optimal selection of maintenance and repair treatments while considering budgetary limits. Additionally, the model uses a non-linear deterioration rate based on the existing conditions of roads, assuming that roads with poorer conditions deteriorate at a faster rate. The developed models are capable of generating color-coded maps of road network showing IRI and pinpointing the locations of anomalies, such as potholes. Additionally, these models are capable of generating action plans to optimize the allocation of funds for the improvement of existing road conditions. The outcome of this research work is expected to reduce inspection cost and enable the capability of generating more frequent maps of roadway pavement conditions. This will assist authorities in allocating funds more efficiently to enhance the performance and functionality of existing transportation networks, based on the most recent information on the conditions of the roads.

4. METHODOLOGY

The research team used low-cost sensors to collect data from road patrol vehicle, including GPS logger, accelerometer and gyroscope, noise recorder, and camera, as shown in Figure 4-1. The collected raw data was analyzed to synchronize data from multiple sensors and recorded videos. Later, the research team manually investigated the videos to identify road surface anomalies that were used to develop supervised machine learning models, including decision trees, random forest, and artificial neural network (ANN). The performance of these models was evaluated on additional collected data to identify the best model based on their accuracy in identifying road surface anomalies. The best model was then used to analyze additional data to generate color-coded maps of road network showing IRI and pinpointing the locations of anomalies, as shown in Figure 4-1.

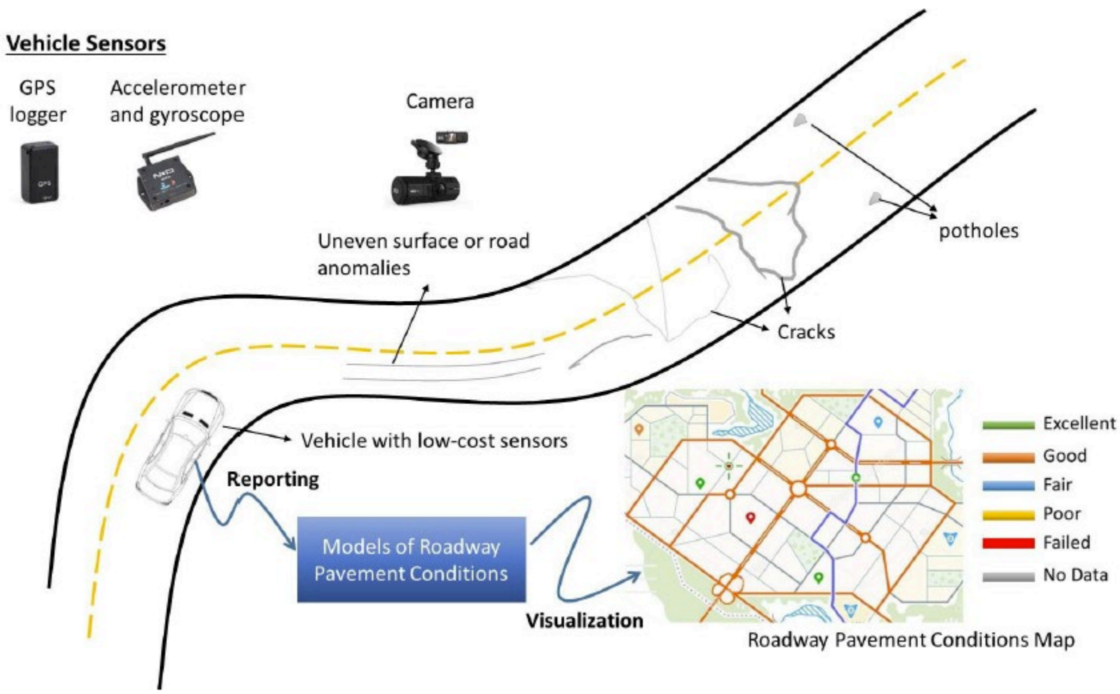

Figure 4.1 System for Reporting Roadway Pavement Conditions

To achieve the objectives of the present research work based on the proposed methodology, five main steps wre followed: (1) data collection; (2) data cleaning and processing; (3) road surface analysis; (4) model development; and (5) performance evaluation, as shown in Figure 4.2. The following sections discuss these steps in details.

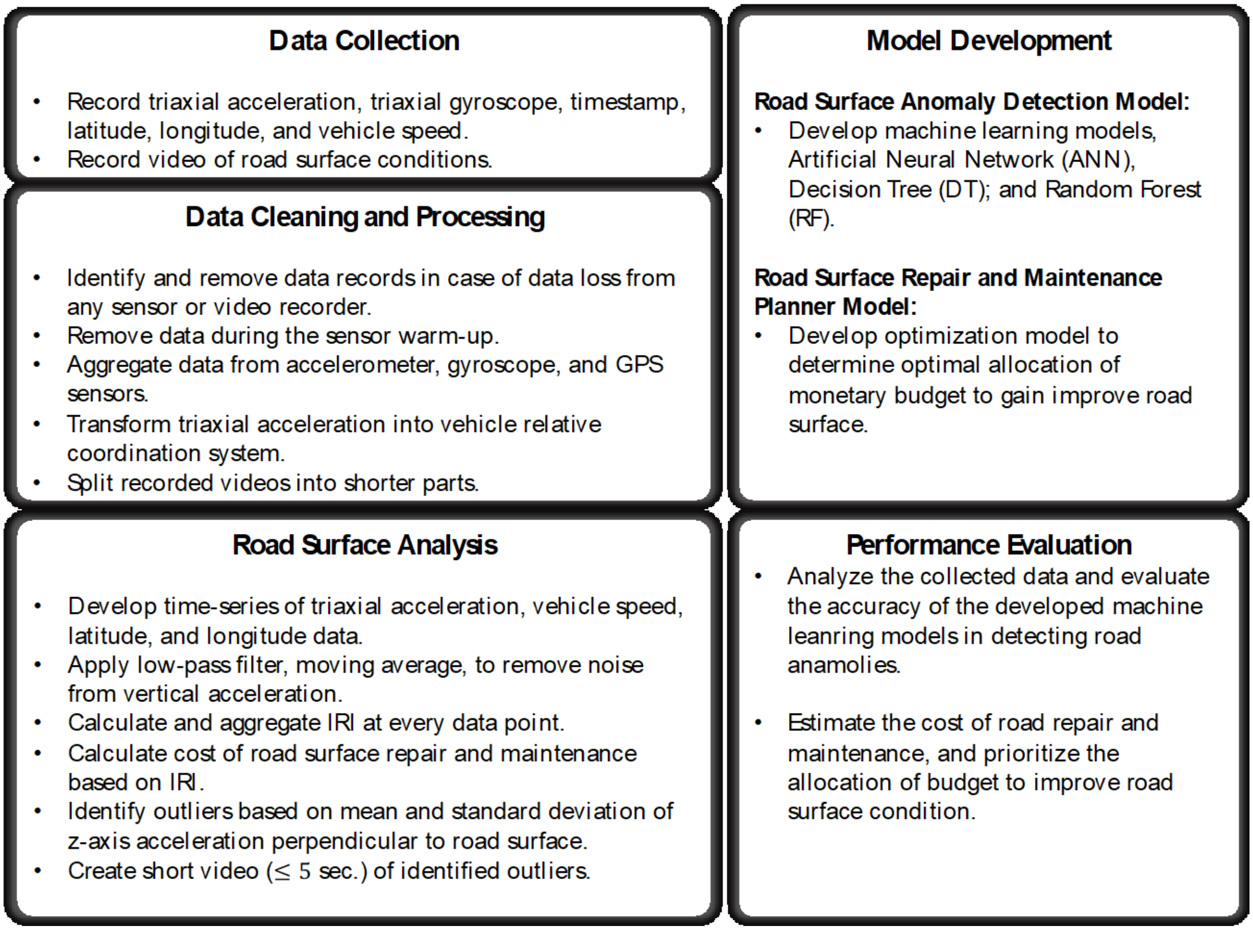

Figure 4.2 Methodology of the present research work

4.1 Data Collection

This step focuses on collecting GPS and accelerometer data from various road conditions. To accomplish this, a multi-sensor device is mounted on the dashboard of a vehicle and a video recorder is installed in front of the vehicle to enable manual detection of road conditions. The collected data includes a diverse set of road surfaces and anomalies and is extensive enough to train machine learning models. It should be noted that while drivers typically try to avoid road irregularities, the driver was instructed to intentionally drive over them for the purpose of data collection. Additionally, to keep the scope of the research limited, data was collected on clear weather days and with the same vehicle type, excluding any effects of weather conditions or vehicle types on the data.

The research team examined the recorded videos of the collected data and identified road anomalies, as shown in Figure 4-3. This process was undertaken to create a training dataset for model development and to assess the accuracy of models in recognizing road anomalies. The data collected comprises of various types of road anomalies such as lateral cracks (45%), lateral joints (17%), longitudinal cracks (16%), repaired areas (11%), manholes (8%), bridge expansion joints (2%), and potholes (1%), as shown in Figure 4-4.

(a) Longitudinal crack

(c) Lateral crack

(d) Manhole

Figure 4.3 Sample of different road anomalies in the database

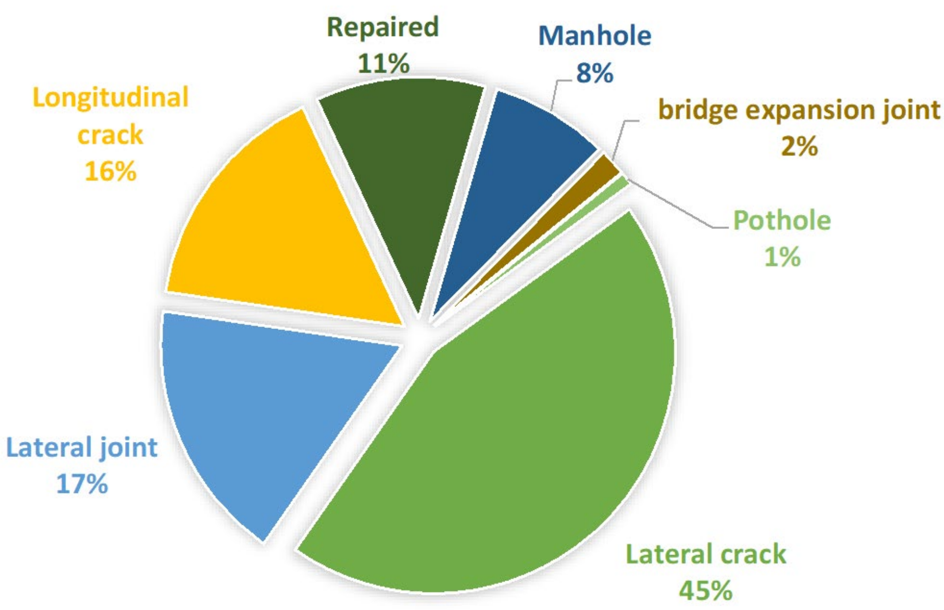

Figure 4.4 Percentage of anomaly types in the collected dataset

4.2 Data Cleaning and Processing

This step focuses on cleaning and processing raw data collected from sensors, including timestamps, latitude, longitude, speed, triaxial acceleration, and triaxial gyroscope. To ensure high-quality data, the first 30 seconds of data collection were disregarded to account for sensor warm-up. Additionally, every sample of collected data was analyzed to remove records with missing data from any other sensors. For example, in cases of weak GPS signals or poor geo-location accuracy, the corresponding data records from other sensors were identified and removed. Furthermore, the triaxial acceleration data is transformed into a vehicle-relative coordinate system, with the z-axis being perpendicular to the road surface. The data from different sensors, which may be in different formats and frequencies, was also aggregated. Finally, recorded videos were split into smaller one-minute chunks, and only the timestamps of the first and last frames were recorded. This was highly useful and computationally efficient when generating snapshots or videos of detected road anomalies, as it significantly reduced the amount of video that must be analyzed.

4.3 Road Surface Analysis

This step focused on identifying potential road anomalies using the processed data discussed previously. To eliminate noise from acceleration data, which may be caused by sudden changes in acceleration, such as braking, we employed a low-pass filter. The filter enabled low-frequency components of the signal to pass through while reducing the amplitude of higher-frequency components, and resulted in a smoothed version of the original signal that was less affected by noise. There are different types of low-pass filters, but the most commonly used is the moving average filter. This filter calculates the average value of a certain number of consecutive data points and replaces the current data point with this average value, effectively eliminating high-frequency noise from the signal as it is unlikely that the noise will persist over multiple consecutive data points. It should be noted that the selection of the filter depends on the type of data, noise level, desired degree of smoothing and the specific requirements of the analysis. The smoothed time-series data was used to calculate the IRI as the square root of the sum of the absolute differences between the vertical acceleration of the vehicle and road surface, divided by the vehicle speed. The condition of road pavement is categorized based on the IRI according to Federal Highway Administration (Federal Highway Administration, 2014).

The developed model was designed to generate color-coded road network based on IRI and pinpoint the location of anomalies, as shown in Figure 4-5. Additionally, the model generated a short video (< 5 seconds) at identified anomaly.

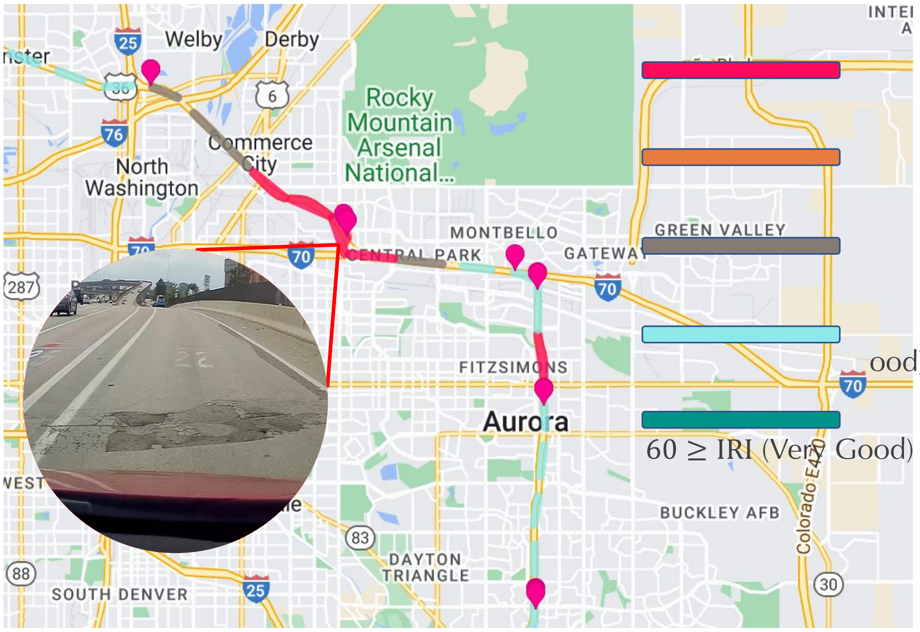

Figure 4.5 Sample of color-coded road network showing IRI and anomaly locations

4.4 Model Development

This step focuses on developing models for (1) road surface anomaly detection; and (2) road surface repair and maintenance planning model, which are discussed separately in the following sections.

4.4.1 Road Surface Anomaly Detection Model

The research team developed three machine learning models, (1) Artificial Neural Network (ANN); (2) Decision Tree (DT); and (3) Random Forest (RF) on detecting road surface anomalies.

4.4.1.1 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) models consist of interconnected layers of artificial neurons, an input layer, one or more hidden layers, and an output layer. Each layer consists of multiple neurons that process and transmit information from one layer to another. In the input layer, the ANN receives data representing average, minimum, and maximum of vehicle, three-axis acceleration, and IRI value. These features are fed into the neurons, which compute weighted sums of the inputs and apply activation functions to produce output values. The hidden layers perform complex calculations on the input data, learning and extracting relevant patterns and relationships. The number of hidden layers and neurons per layer can be adjusted based on the complexity of the anomaly detection task. The output layer of the ANN model classifies the road surface anomalies. The weights and biases of the neurons are iteratively adjusted during the training process, using techniques such as backpropagation, to minimize the difference between the predicted output and the actual ground truth. The functionality of ANN models lies in their ability to learn and generalize from training data. By iteratively adjusting the weights and biases based on training examples, the ANN model gradually improves its ability to accurately detect anomalies in road surfaces. Once trained, the model can then process unseen road surface data and make predictions or classifications with high accuracy.

4.4.1.2 Decision Tree (DT)

Decision Tree (DT) is a widely used supervised classification machine learning model where each node in the tree represents a feature or attribute, each branch represents a decision or rule, and each leaf represents the outcome or prediction. The topmost node in the decision tree is known as the root node. The goal of a decision tree is to predict the value of a target variable by learning simple decision rules inferred from the data features. The decision tree algorithm starts with the root node and recursively splits the data into subsets based on the values of the input features, creating internal nodes and branches in the process. The algorithm continues this process until it reaches a leaf node, which represents the final prediction.

4.4.1.3 Random Forest (RF)

Random Forest is an ensemble learning method that utilizes multiple decision trees to create a robust model. It enhances anomaly detection accuracy by training subsequent decision trees to focus on identifying anomalies missed by previous trees. One key advantage of Random Forest is its effectiveness in handling imbalanced datasets, where anomalies are infrequent compared to normal conditions. Traditional machine learning algorithms struggle with imbalanced data, but Random Forest overcomes this challenge. Its ability to generate multiple decision trees and aggregate their outputs enables superior handling of imbalanced classes, leading to improved detection performance for road surface anomalies.

4.4.2 Optimizing Road Maintenance & Repair (M&R)

This section focuses on developing a mixed integer linear programing (MILP) optimization model for optimizing the plan and schedule of M&R strategies over time, while considering annual budgetary limits. The optimization model is developed in four main steps: (1) identifying decision variables; (2) defining objective function; (3) formulating constraints; and (4) executing model computations. These steps are discussed as follows:

4.4.2.1 Decision variables

The road network is divided into segments of a fixed length, usually around one mile, and these segments are analyzed over a specific time period, typically 10 years. While it is possible to use shorter or longer segments for analysis, long segments do not accurately capture the variations in pavement conditions since they become less uniform. On the other hand, short segments create too much detail and lead to excessive variations in pavement condition across the road network, making the model complex and difficult to handle due to the increased size. Initially, these segments are assigned to have the same condition as the existing IRI values. At the end of each year, the IRI of a segment can either deteriorate or improve, depending on the chosen maintenance and repair (M&R) strategy for that particular year. The M&R strategies include a range of options, including, but not limited to, preventive maintenance, which is the simplest and least expensive option, to rehabilitation, which is the most complex and costly alternative. Therefore, it is necessary to identify decision variables that effectively model the planning of M&R strategies for each road segment on an annual basis.

One group of decision variables, $x_{i,t,m}$, is identified to model the selection of M&R strategies over time for the entire road network. Accordingly, $x_{i,t,m}$ is a binary decision variable that is 1 if mth M&R strategy is selected at year t and road segment i; and 0 otherwise, as shown in Figure 4-6. M&R strategies have different costs and reduce IRI at certain amounts. For example, a simple preventative maintenance might cost $16,000 and reduce IRI by 19 inch/mile; whereas a light rehabilitation might cost $130,000 and reduce IRI by 76 inch/mile. The selection of M&R strategies depends on the available annual budget and improvement of road condition in terms of reduced IRI. If no M&R strategies are selected, the condition of road segment degrades by increasing the IRI. The degradation can be modeled at a fixed or variable rate, depending on the current road condition, which will be discussed in the following sections. The identified decision variables are capable of modeling the selection of M&R strategies on an annual basis for each road segment and quantifying the corresponding IRI values.

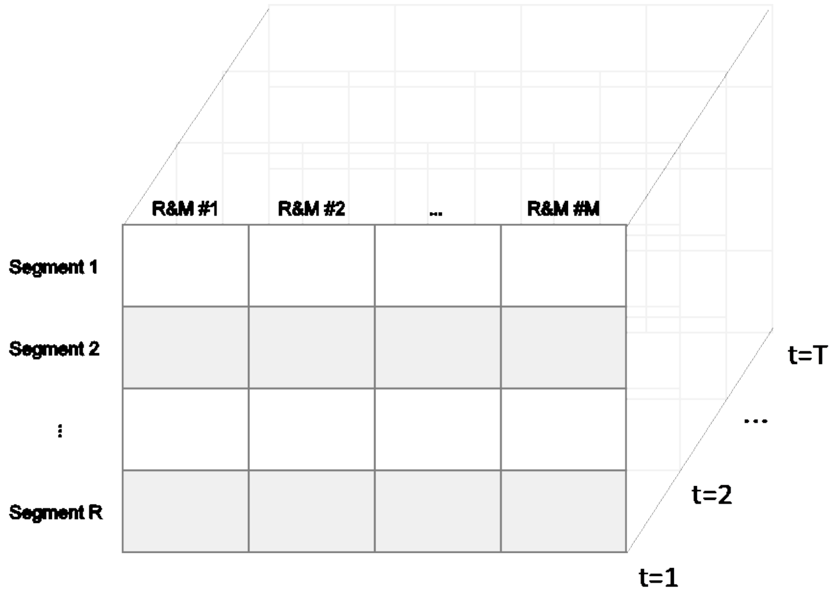

Figure 4.6 Identified decision variables

4.4.2.2 Constraints

The constraints in the model are formulated to ensure feasibility of the generated plan and schedule of M&R strategies within the annual budgetary limit. These groups of constraints include:

- C1 ensures that only one M&R strategy is selected, at most, for each road segment, with the possibility of no strategy being selected.
- C2 ensures that the IRI at each road segment is reduced in accordance with the chosen M&R treatment, while ensuring it does not fall below a specified threshold. This threshold can be defined as the minimum acceptable IRI for a road segment. For example, it can be set at 60 inches per mile. In addition, it ensures that if no M&R treatment gets selected, the road condition degrades at a predefined rate.
- C3 ensures that for a given road segment, M&R strategies cannot be selected in two consecutive years. This constraint helps maintain a reasonable time gap between M&R activities on the same segment.
- C4 ensures that the total cost of selected M&R strategies in each year remains within the annual budget. This constraint prevents the cumulative cost from exceeding the available financial resources.

4.4.2.3 Objective Function

The objective function is designed to quantify the total IRI of the road network for a predefined study period. While the initial IRI of roads are set at the existing road conditions, the IRI of road network reduces according to the selected M&R strategies of each year. However, to account for deterioration of road segments at each year, a fixed rate, λ is considered to increase the IRI of the road segments over time. For example, λ can be set at 15 inch/mile to increase the IRI of the road segments at each year. While λ depends on several factors, such as traffic loads, climate and weather conditions, and construction quality of pavement, a fixed rate is often used to generalize and simplify M&R budgetary planning. However, this assumption is quite simplified and does not reflect the impact of current road condition on its deterioration rate. It is generally the case that as the IRI of a road segment increases, the deterioration rate also increases. This assumption is then addressed in the following sections.

$$f(x): \quad \sum_{i=1}^{R}\left(IRI_{i,t=0} - \sum_{t=1}^{T}\sum_{m=1}^{M}\left(\alpha_m x_{i,m,t}\right)\right) + \lambda \sum_{i=1}^{R}\sum_{t=1}^{T}\left(1 - \sum_{m=1}^{M} x_{i,m,t}\right)$$

$$\text{C1:} \quad \sum_{m=1}^{M} x_{i,m,t} \leq 1 \qquad \forall\, t \in \{1,2,\dots,T\} \quad \forall\, i \in \{1,2,\dots,R\}$$

$$\text{C2:} \quad IRI_{i,t=0} - \sum_{t=1}^{L}\sum_{m=1}^{M}\left(\alpha_m x_{i,m,t}\right) + \lambda \sum_{t=1}^{L}\left(1 - \sum_{m=1}^{M} x_{i,m,t}\right) \geq IRI^{*} \qquad \forall\, L \in \{1,2,\dots,T\} \quad \forall\, i \in \{1,2,\dots,R\} \quad \forall\, m \in \{1,2,\dots,M\}$$

$$\text{C3:} \quad \sum_{m=1}^{M} x_{i,m,t+1} \leq 1 - \sum_{m=1}^{M} x_{i,m,t} \qquad \forall\, i \in \{1,2,\dots,R\} \quad \forall\, t \in \{1,2,\dots,T-1\}$$

$$\text{C4:} \quad \sum_{i=1}^{R}\sum_{m=1}^{M}\left(c_m x_{i,m,t}\right) \leq B_t \qquad \forall\, t \in \{1,2,\dots,T\}$$

$$x_{i,m,t} \in \{0,1\}$$

Where, $IRI_{i,t=0}$ is the IRI for road segment i at time $t = 0$; T is the number of years in the study period; R is the number of road segments; $x_{i,m,t}$ is a binary decision variable that indicates if mth M&R strategy is selected or not at year t and road segment i; c_m is the cost of mth M&R strategy; λ is a fixed deterioration rate at which the IRI increases over time.

As mentioned above, the deterioration rate, λ in the model above is set at a fixed rate. However, in real practice, the deterioration rate is non-linear depending on IRI, as shown in Figure 4.7. For road segments with an IRI below 60 inches per mile (indicating good condition), the deterioration rate remains constant at three inches per mile. In the range of 60 to 94 inches per mile, the deterioration rate varies at a constant rate. Beyond this range, the deterioration rate increases further, reaching a constant rate for road segments in poor condition (IRI > 220 inches per mile). This non-linear relationship between IRI and the deterioration rate reflects the deterioration more accurately.

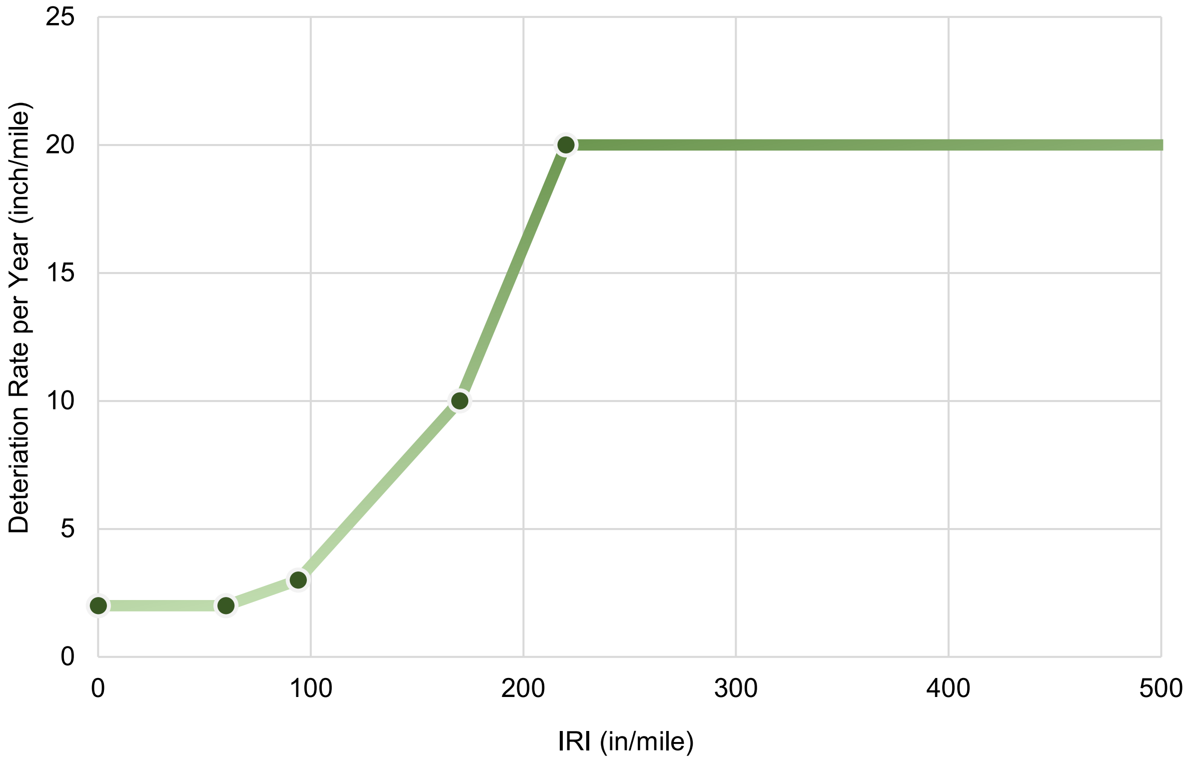

Figure 4.7 Deterioration rate as a function of IRI

To model the non-linear deterioration rate for road segments, a piecewise linear function is used to determine the deterioration rate for each road segment based on its IRI. Accordingly, two other types of decision variables, $y_{i,j,t}$ and $z_{i,j,t}$, are identified, where $y_{i,j,t}$ is a nonnegative continuous decision variable used to impose a linear combination at each interval of the piecewise linear function. $z_{i,j,t}$ is a binary decision variable used to impose that at most two of the $y_{i,j,t}$ can be nonzero. Accordingly, several other constraints are formulated in the model. C5 ensures that the sum of $y_{i,j,t}$ are equal to one; C6, C7, C8 are other groups of constraints that impose the relationship between the $y_{i,j,t}$ and $z_{i,j,t}$. Finally, C9 ensures that IRI of road segments are initially set at the existing condition, and C10 ensures IRI of road segments are improved or degraded. It should be noted that the last M&R treatment, "Reconstruction", is excluded from C9 and C10. The reason is that when a road segment gets reconstructed, its IRI drops to the lowest IRI value, regardless of the pre-construction IRI value.

$f(x)^*$: $$\sum_{i=1}^{R}\sum_{t=1}^{T} IRI_{i,t=0} - \sum_{m=1}^{M-1}\left(\alpha_m x_{i,m,t}\right) + \left(2y_{i,1,t} + 3y_{i,2,t} + 10y_{i,3,t} + 20y_{i,4,t} + 20y_{i,5,t}\right)$$

C2*: $60y_{i,1,t} + 95y_{i,2,t} + 170y_{i,3,t} + 220y_{i,4,t} + 1000y_{i,5,t} \geq IRI^*$ $\quad \forall\, i \in \{1,2,\dots,R\}$, $\forall\, t \in \{1,2,\dots,T\}$

C5: $y_{i,1,t} + y_{i,2,t} + y_{i,3,t} + y_{i,4,t} + y_{i,5,t} = 1$ $\quad \forall\, t \in \{1,2,\dots,T\}$, $\forall\, i \in \{1,2,\dots,R\}$

C6:
$$\begin{aligned} y_{i,1,t} &\leq z_{i,1,t} \\ y_{i,2,t} &\leq z_{i,2,t} \\ y_{i,3,t} &\leq z_{i,3,t} \\ y_{i,4,t} &\leq z_{i,4,t} \\ y_{i,5,t} &\leq z_{i,5,t} \end{aligned} \qquad \forall\, t \in \{1,2,\dots,T\},\ \forall\, i \in \{1,2,\dots,R\}$$

C7: $z_{i,1,t} + z_{i,2,t} + z_{i,3,t} + z_{i,4,t} + z_{i,5,t} \leq 2$ $\quad \forall\, t \in \{1,2,\dots,T\}$, $\forall\, i \in \{1,2,\dots,R\}$

C8:
$$\begin{aligned} z_{i,1,t} + z_{i,3,t} &\leq 1 \\ z_{i,1,t} + z_{i,4,t} &\leq 1 \\ z_{i,1,t} + z_{i,5,t} &\leq 1 \\ z_{i,2,t} + z_{i,4,t} &\leq 1 \\ z_{i,2,t} + z_{i,5,t} &\leq 1 \\ z_{i,3,t} + z_{i,5,t} &\leq 1 \end{aligned} \qquad \forall\, t \in \{1,2,\dots,T\},\ \forall\, i \in \{1,2,\dots,R\}$$

C9:
$$\begin{aligned} &60y_{i,1,t} + 95y_{i,2,t} + 170y_{i,3,t} + 220y_{i,4,t} + 1000y_{i,5,t} \\ &\quad \geq IRI_{i,t=0} - \sum_{m=1}^{M-1}\left(\alpha_m x_{i,m,t}\right) - M * x_{i,M,t} \\ &\quad + \left(2y_{i,1,t} + 3y_{i,2,t} + 10y_{i,3,t} + 20y_{i,4,t} + 20y_{i,5,t}\right) \end{aligned} \qquad t = 1,\ \forall\, i \in \{1,2,\dots,R\}$$

C10:
$$\begin{aligned} &60\left(y_{i,1,t} - y_{i,1,t-1}\right) + 95\left(y_{i,2,t} - y_{i,2,t-1}\right) + 170\left(y_{i,3,t} - y_{i,3,t-1}\right) + 220\left(y_{i,4,t} - y_{i,4,t-1}\right) \\ &\quad + 1000\left(y_{i,5,t} - y_{i,5,t-1}\right) \\ &\quad \geq 2y_{i,1,t} + 3y_{i,2,t} + 10y_{i,3,t} + 20y_{i,4,t} + 20y_{i,5,t} - \sum_{m=1}^{M-1}\left(\alpha_m x_{i,m,t}\right) - M \\ &\quad * x_{i,M,t} \end{aligned} \qquad \forall\, t \in \{2,\dots,T\},\ \forall\, i \in \{1,2,\dots,R\}$$

5. FEASIBILITY ANALYSIS OF WIDESPREAD APPLICATION

The results of the analyzed case study and performance of the developed models show promising application of such models to be widely used. For example, installing low-cost sensors at police patrol vehicles and/or taxi vehicles to generate maps of roadway pavement conditions. For example, Eriksson et al, analyzed practicality of using a system where drivers can opt in and have vibration and GPS sensors installed on their vehicles to assess road surface conditions. The system was deployed on seven taxis in the Boston area and used machine-learning models to identify potholes and other severe road surface anomalies (Eriksson et al., 2008). However, the developed model was not tested on a larger scale, and its results are not clear. Additionally, little work was conducted to analyze the willingness of drivers to sign up for such systems, especially, in the absence of incentives. One major challenge of widespread application of sensing devices for road surface assessment is the concern of privacy on collected data. To address this challenge, Basudan et al. developed a privacy-preserving protocol for enhancing security in a vehicular crowdsensing-based road surface condition monitoring system (Basudan et al., 2017). However, the model was not integrated into existing road surface assessment models, and it is not clear how challenging and computationally expensive it is to integrate security protocols in data collection for road surface assessment. One key factor of successful widespread application of road surface assessment models is to use widely accessible sensor devices, such as cellphones. The built-in accelerometer, gyroscope, and GPS sensors of smartphones are low-cost and widely accessible tools anyone can use for collecting data. For example, Singh et al. developed computationally efficient machine learning that can be installed on different types of devices with a high detection accuracy of over 85% (Singh et al., 2017).

The feasibility of widespread application of sensor devices for road surface assessment and anomaly detection depends on a variety of factors, including the cost and durability of the sensors, ability to accurately interpret sensor data, and infrastructure and resources available for deploying and maintaining the sensors. Additionally, it also depends on the legal and regulatory framework and potential benefits of using these sensors. However, it is likely that sensor technology will continue to improve and become more widely adopted in the future, making it more feasible for widespread application of sensor devices for road surface assessment and anomaly detection. The combination of sensors like LIDAR, cameras, and ultrasonic sensors, deep learning and AI techniques can provide high accuracy and real-time road surface condition and anomaly detection.

6. CASE STUDY

To evaluate performance of the developed models and demonstrate their capabilities in identifying road conditions and the optimal schedule and plan for M&R, a case study of road network in Denver, CO, is analyzed. The case study consists of a 172 lane miles of urban road network. Approximately, 87% of the lane miles were either in “Very Good,” “Good,” “Fair,” and “Poor” condition, whereas nearly 11% of the roads were in “Mediocre” condition, as shown in Figure 6.1.

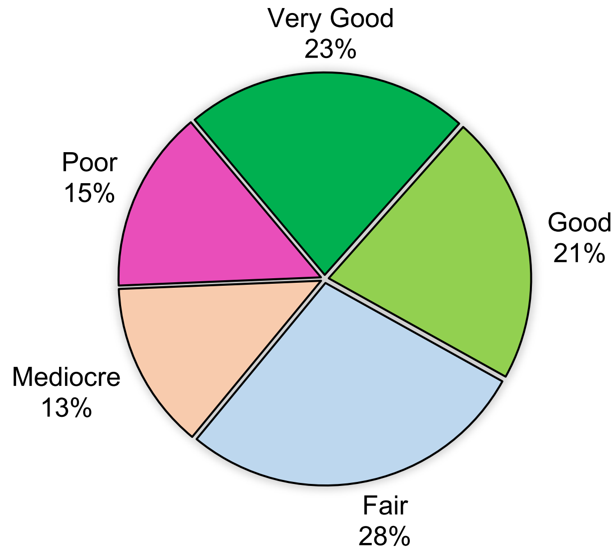

Figure 6.1 Percentage of lane miles

To evaluate performance of the developed machine learning models and measure their accuracy in identifying road surface anomalies, additional dataset of road surface conditions not used during the model development were analyzed. Table 6.1 shows the accuracy of the developed models in identifying road anomalies on train and test datasets. To avoid overfitting in the models, the early termination was enforced to stop training after 100 iterations. In all cases, accuracy of the models decreased on test dataset compared to that of train dataset, since the train dataset was used during the model development and the model performance is evaluated based on that. RF model has the highest accuracy in identifying road anomalies. The reason is that the RF is a more adaptive to capture non-linearity of the data, and it consists of multiple DT models. The ANN model had the lowest accuracy due to the imbalanced dataset.

Table 6.1 Performance of the developed models

Model	Accuracy (%)	
	train dataset	test dataset
ANN	76.4%	67.2%
DT	84.8%	78.4%
RF	91.1%	83.6%

Table 6.2 shows the different M&R treatments with their corresponding reductions in IRI and unit costs (Saha & Ksaibati, 2018). Preventive maintenance M&R is a periodically and low-cost treatment to improve the current road condition slightly. However, light, and medium rehabilitation M&R improve the road condition even further and are generally used to upgrade the road condition by one or two levels, respectively. The last M&R level reconstructs the road and improves the IRI according to the threshold for very good category.

Table 6.2 M&R treatments and corresponding reduction in IRI (Saha & Ksaibati, 2018)

Treatment	M&R actions	IRI reduction (inch/mile)	M&R treatment unit cost ($/mile)
Preventive maintenance	Slurry seal and microsurfacing	19	16,000
Light rehabilitation	5 cm milling, 4-6 cm hot mix asphalt (HMA) overlay	76	52,000
Medium rehabilitation	10 cm milling, 8-12 cm hot mix asphalt (HMA) overlay	127	160,000
Heavy rehabilitation	Reconstruction	Regardless of road condition, IRI reaches at 60	800,000

Results of the optimization model, based on different annual budgets, provide valuable insights into the changes in the International Roughness Index (IRI) over time and demonstrate the impact of maintenance and repair (M&R) treatments on the road network's condition. For an annual budget of $400,000, the initial IRI is 133. Despite the implementation of M&R treatments, the degradation rate of the road network is higher than the rate of improvement, resulting in an average increase in the IRI over the 10-year period. The final IRI reaches 173.9, indicating a worsening road condition, as shown in Figure 6-2. As the annual budget increases to $600,000, the positive impact of M&R treatments becomes evident. The IRI steadily decreases over time, resulting in a final IRI of 146.8 after 10 years. With a budget of $800,000, the IRI experiences further improvement, reaching a final value of 124.0. The higher budget allows for more extensive M&R treatments, effectively slowing down the deterioration process, as shown in Figure 6-2. Increasing the budget to $1 million leads to a significant improvement in the IRI, with the final value decreasing to 104.5. This highlights the importance of adequate budget allocation for achieving substantial road network improvements. Notably, when the budget reaches $1.5 million and $2 million, substantial improvements in the road network's condition are observed. The IRI values decrease significantly, reflecting the positive impact of higher budgets and more extensive M&R treatments. The final IRI after 10 years for the $1.5 million budget is 65.7, while 61 IRI for the $2 million budget, as shown in Figure 6-2. These results demonstrate the critical role of budget allocation for M&R activities in maintaining and improving road conditions. Higher budgets allow for more comprehensive and frequent M&R treatments, leading to significant reductions in the IRI over time. Thus, appropriate budget planning and allocation are crucial for ensuring the sustainability and longevity of road networks.

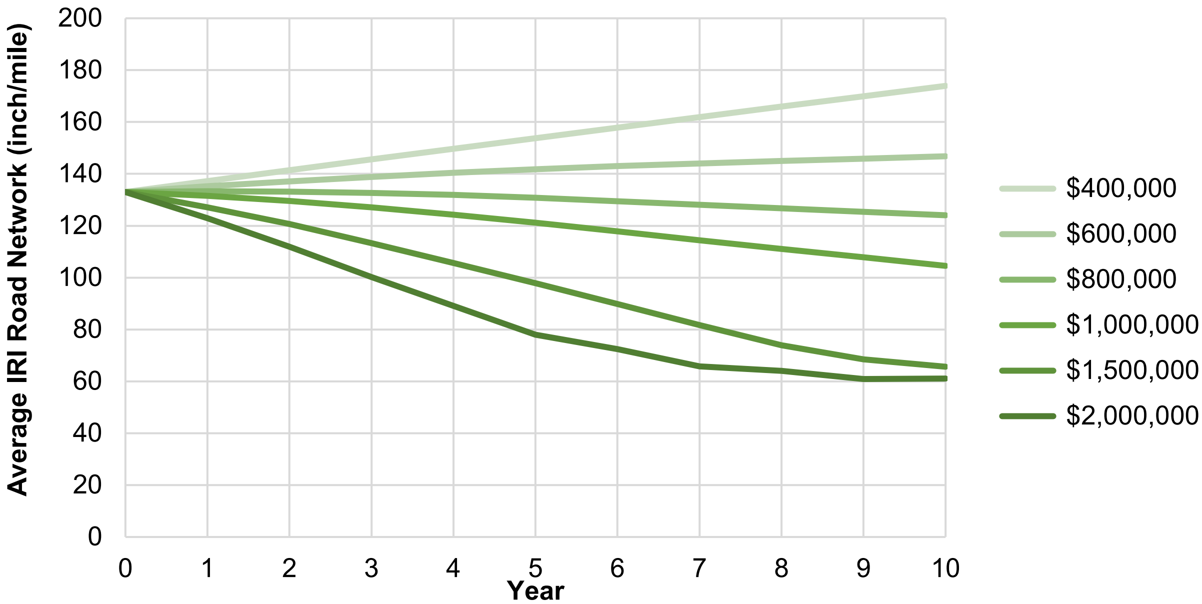

Figure 6.2 Average IRI for various budget scenarios

The outcome of the model can provide valuable insights on identifying sufficient budgets to maintain and enhance road conditions. There is a tipping point where the degradation of the road network is the same as the rate of road condition improvement, as shown in Figure 10. Adequate funding allows for more comprehensive and proactive M&R strategies, slowing deterioration and extending the lifespan of road infrastructure. This emphasizes the importance of avoiding underfunding, as it can lead to a decline in road conditions and increased costs in the long run.

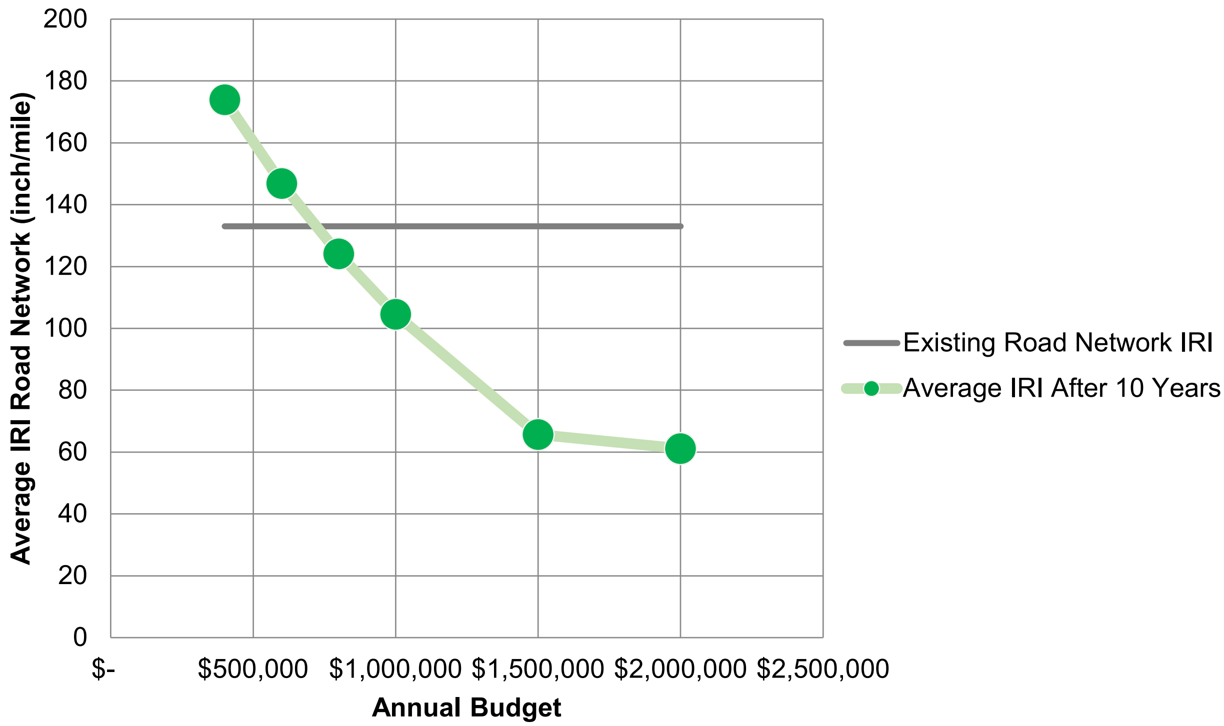

Figure 6.3 Impact of different annual budget on average IRI after 10 years

The road segments are categorized under different conditions for the existing condition, at year five, and at year 10, based on the identified optimal M&R treatment with a budget of $2 million per year, as shown in Figure 11. At the existing condition, the road network is distributed across various road condition categories. Approximately 23% (39 miles) of the roads are classified as "Very Good," 21% (37 miles) as "Good," 28% (48 miles) as "Fair," 13% (23 miles) as "Mediocre," and 15% (25 miles) as "Poor." These percentages provide a baseline for assessing the effectiveness of the M&R treatment plan. After five years of implementing the optimal M&R treatment plan, there are noticeable changes in the road conditions. The percentage of roads in the "Very Good" category increases to 38% (65 miles), indicating an improvement. The "Good" category shows a substantial increase to 53% (91 miles), suggesting a significant positive impact. However, there are still areas that need improvements. The percentage of roads in the "Fair" category is 4% (eight miles), while the "Mediocre" and "Poor" categories decrease to 3% (five miles) and 2% (three miles), respectively. Looking ahead to the 10-year mark, the road conditions undergo a remarkable transformation. The percentage of roads in the "Very Good" category increases to 100% (172 miles), indicating a complete transition to a higher quality category. Furthermore, the percentages of roads in the "Good," "Fair," "Mediocre," and "Poor" categories drop to 0%, indicating the successful revitalization of the road network. These results demonstrate effectiveness of the optimal M&R treatment plan in improving the road conditions over a 10-year planning period. The plan effectively targets the roads in need of maintenance and rehabilitation, resulting in a significant increase in the percentage of roads in better conditions. The complete elimination of roads in lower-quality categories signifies a successful outcome in terms of road network revitalization.

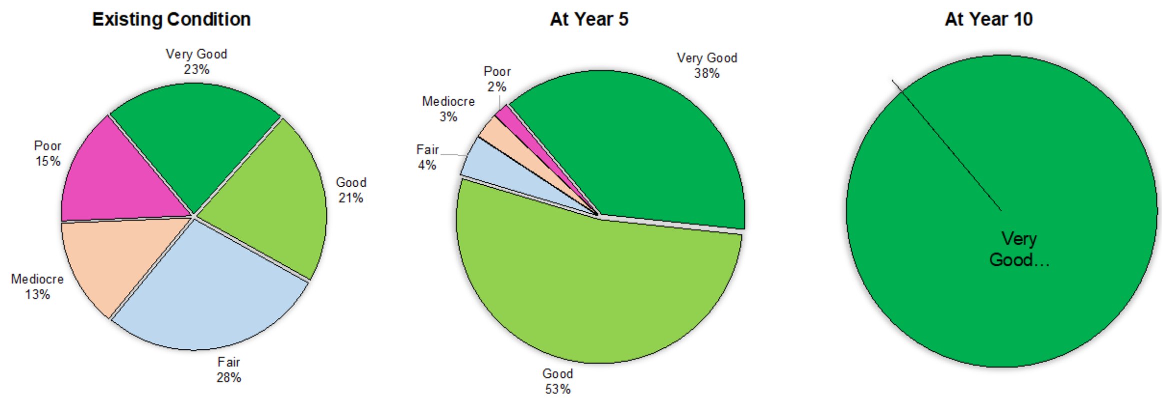

Figure 6.4 Road conditions for the existing condition, at year five, and at year 10 based on the identified optimal M&R treatment with an annual budget of $2 million

Miles of untreated roads along with treated ones for the identified optimal M&R treatment with a budget of $2 million per year, are shown in Figure 12. In the first year, the majority of the roads, 133 miles, were left untreated with the "Do nothing" approach. A small portion received preventive maintenance (2 miles), and 37 miles underwent light rehabilitation. There were no instances of medium or heavy rehabilitation during this year. In the following years, we observe variations in the distribution of M&R treatments. The number of miles left untreated gradually decreases, as the "Do nothing" category decreases over time. This indicates a shift toward proactive maintenance strategies. Preventive maintenance and light rehabilitation efforts show a relatively steady pattern, with slight fluctuations in the number of miles treated. Notably, in year six, there was a significant increase in the miles receiving preventive maintenance (71 miles), suggesting a more proactive approach to road preservation. In year seven, we observed a rise in miles receiving medium rehabilitation (12 miles) and a small number of miles undergoing heavy rehabilitation (three miles). This indicates a need for more extensive interventions to address road deterioration in specific areas. The following years show a varying distribution of M&R treatments. Preventive maintenance and light rehabilitation continue to be applied, although with some fluctuations in the number of miles treated. Medium rehabilitation efforts decrease, while heavy rehabilitation becomes less prevalent, with only sporadic instances. At the 10-year mark, the M&R treatment plan reflects a balance between proactive strategies and targeted rehabilitation. The "Do nothing" category has significantly decreased, indicating a proactive approach to road maintenance. Preventive maintenance and light rehabilitation remain the primary treatments, suggesting a focus on preserving and improving road conditions before they deteriorate further. Overall, the results demonstrate a shift toward more proactive maintenance strategies over time. The M&R treatment plan prioritizes preventive measures, such as regular maintenance and light rehabilitation, to address issues before they become severe. This approach helps extend the lifespan of roads and minimize the need for extensive and costly rehabilitation efforts.

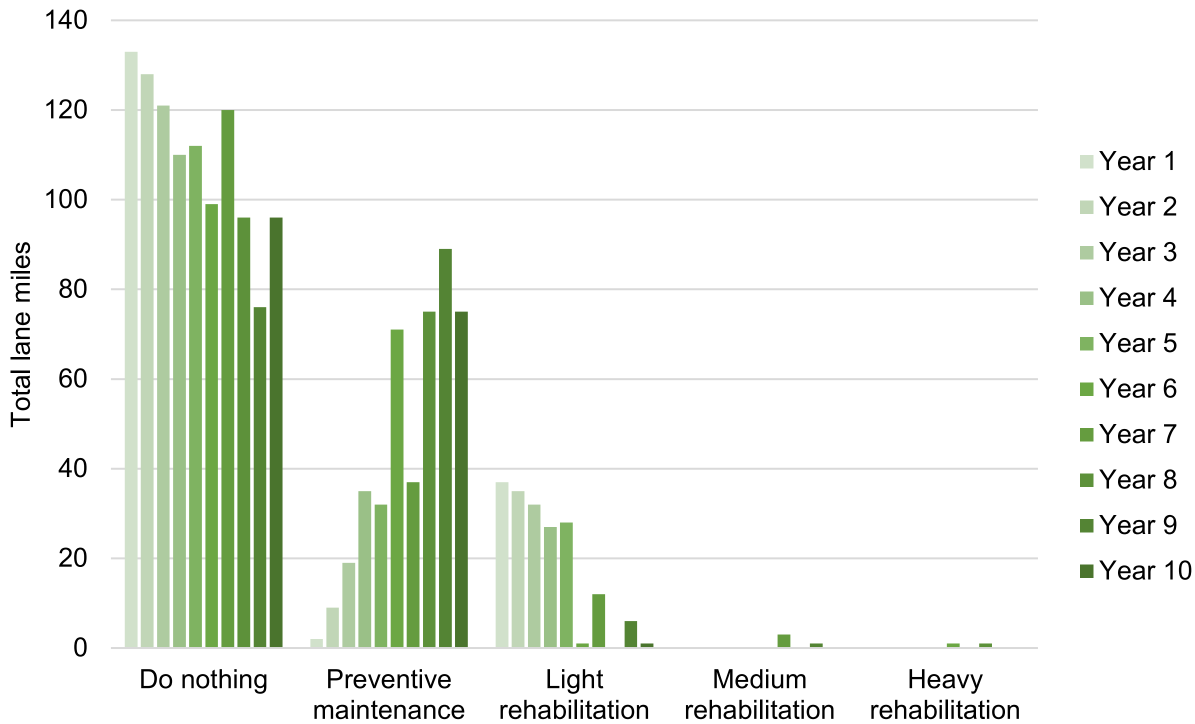

Figure 6.5 Miles treated with the optimal M&R plan based on the solution with an annual budget of $2 million

The IRI of road segments over time for the identified optimal M&R treatment with a budget of $2 million per year, are shown in Figure 13. The general trend of road segments indicates an improvement in road conditions, as evidenced by decreases in IRI. This positive change is due to maintenance and repair treatments implemented on these segments. However, it is important to note for certain road segments where no maintenance and repair treatments were applied, the IRI slightly increases at a fixed rate each year to account for degradation based on their existing road condition. This suggests that without regular maintenance interventions, these segments experience gradual deterioration over time.

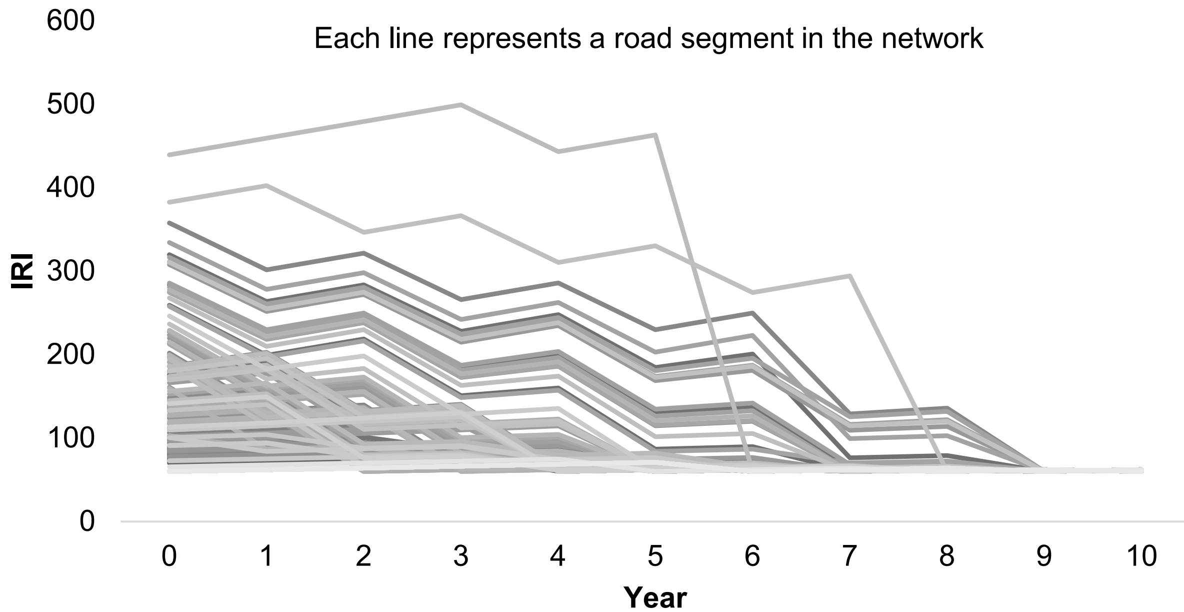

Figure 6.6 IRI of road segments over time based on the identified optimal M&R treatment with a budget of $2 million per year

7. CONCLUSIONS AND SUMMARY

This research work presented the development of models for road surface anomaly detection and optimization of maintenance and repair (M&R) interventions. The research team collected data using low-cost and widely accessible GPS, gyroscopes, accelerometer. The data were then processed and analyzed to prepare input data for supervised machine learning classification models, where the data was meticulously analyzed, and road anomalies were classified. This allowed the development of a baseline for evaluating the performance of machine learning models. Three machine learning models, (1) Artificial Neural Network (ANN); (2) Decision Tree (DT); and (3) Random Forest (RF) were developed. Using the collected data and identified anomalies, the performance of these model and their accuracy in identifying road anomalies were evaluated. The RF model reported the highest accuracy in identifying road anomalies at 83.6%, while ANN reported the lowest accuracy. The reason for better performance of RF model compared to others is the capability of handling unbalanced input dataset where the number of anomalies compared to normal road conditions is insignificant. Additionally, RF models are assembly of multiple DT models, where each DT model improves the classification of previous DT models.

Furthermore, this research presented the development of a mixed integer linear programing (MILP) optimization model for optimizing the plan and schedule of M&R strategies over time, while considering annual budgetary limits. The optimization model was developed in four main steps: (1) identifying decision variables; (2) defining objective function; (3) formulating constraints; and (4) executing model computations. Decision variables were identified to model the selection of M&R strategies for each road segment on an annual basis, while constraints were formulated to ensure feasibility and budgetary limits. The objective function quantified the total International Roughness Index (IRI) of the road network over time, accounting for deterioration and M&R interventions. Notably, the degradation of road segments was modeled using a piecewise linear function that captured the non-linear relationship between IRI and deterioration rate. The optimization model provided valuable insights into the impact of different annual budgets on road conditions over a 10-year period. It revealed that adequate funding was crucial for maintaining and enhancing road conditions. The findings indicated a tipping point where the degradation of the road network was equivalent to the rate of improvement. Underfunding led to a decline in road conditions and increased costs in the long run. However, with sufficient budgets, the model demonstrated significant improvements in road conditions over time. The results based on the solution obtained for an annual budget of $2 million, showed that all the roads in the analyzed case study will reach to “Very good” condition after 10 years.

Finally, the feasibility of widespread application of sensors on smartphone devices was discussed. While the research team identified possible potentials of the widespread application of such models, there is no practical solution yet that addresses the data privacy concerns of road users, and lack of motivation for participants. One research area of interest is to analyze the feasibility of tax deduction, or tax credits for participants that report road conditions using low-cost sensors. Future research is needed to expand the capabilities of the detection and optimization models to increase the accuracy of detecting road conditions and scheduling their maintenance in a large network and within available budget.

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