

Leveraging Artificial Intelligence for Optimal Maintenance and Rehabilitation Decisions in Pavement ManagementDeep Patel¹, Dr. Piyush J. Patel²*Research scholar, Sankalchand Patel University, Visnagar, India¹**Principal, Sankalchand Patel College of Engineering, Visnagar, India²***Abstract:**

An efficient pavement management system is essential for ensuring the highest level of road user comfort and safety on urban arterials, which are the primary objectives of transportation. Traditional pavement management systems generally rely on periodic manual inspections, which uses more resources, time consuming and are reactive in nature. In this study, a proactive solution for pavement maintenance management based on machine learning and artificial intelligence is presented. Cracks and Potholes are the two most observed major distresses observed in urban roads. Cracks and Potholes significantly affect design life and maintenance cost of pavement and hence it is necessary to develop effective prediction system. For Distress prediction modelling using machine learning technique, distress data has been collected using mobile camera from 21 road sections in Ahmedabad city. Traffic volume data, rainfall data and periodic maintenance data were also collected from concerned urban local body. Distresses were classified and severity of distresses measured according to IRC 82-2015 guidelines by employing You Only Look Once architecture. To predict future deteriorations, predictive modelling employed using Support Vector Regression. This study combines Artificial Intelligence with the Analytic Network Process to improve multi-criteria decision-making which helps authorities for making decisions about how to maintain city roads. Proposed decision support framework prioritizes overall maintenance by considering intensity of traffic and street type based on cost effectiveness. This framework would help authorities to shift from a reactive "fix-it-when-it-fails" model to a proactive, predictive maintenance strategy.

Keywords: Artificial Intelligence, Pavement Management System, Machine Learning, Predictive Maintenance, Infrastructure, Decision Support System.

I. Introduction

The rise in urbanisation around the world has put more stress on city road networks than ever before. Urban roads are no longer only ways to get from one place to another; they are backbone of the economy and society. But standard pavement management systems (PMS) can't keep up with the fast deterioration caused by more traffic, harsh weather patterns caused by climate change, and materials that are getting older [16]. Most of urban local bodies in India conducts road inspections manually, which is known to be subjective, dangerous for workers, and too expensive for big metropolitan networks [13],[14].

Poor maintenance has two effects: higher long-term expenses because of "delayed repair" premiums and bigger carbon footprints because of traffic jams and constant maintenance [12]. As cities attempt to become "Smart Cities," they require a framework that can automatically, objectively, and on a large scale sense, anticipate, and prioritise pavement repairs in real time [11], [15].

In urban pavement management, identifying the most frequently observed failures is critical for developing precise AI-driven maintenance models. Most prevalent distresses in urban areas are **potholes** and various forms of **cracking**, particularly **longitudinal and alligator (fatigue) cracking** [1],[3]. Potholes often dominate urban pavement failures, sometimes accounting for over 40% of observed distress in city centers, frequently triggered by localized disintegration following water infiltration through untreated cracks [2]. **Edge failure and rutting**, which is sometimes made worse at junctions by severe breaking and stop-and-go traffic. Furthermore, urban-specific factors such as utility cuts and subsequent poor patching lead to significant surface irregularities and structural weaknesses [2], [14]. Statistical analysis of significant urban road networks indicates that, longitudinal cracking, ravelling, rutting, patching, and fatigue cracking are five principal distress types which constitute almost 97% of bituminous pavement failures [6],[8]. Joint spalling, faulting, and pumping are the most common problems in rigid pavement sections [9]. AI based automated detection systems are increasingly focusing on these high-frequency problems to calculate the Pavement Condition Index (PCI) [6],[8]. This allows urban local bodies to move from reactive to proactive maintenance strategies by fixing these common problems before they lead to complete structural failure [7], [10]. The first step in a modern PMS is to correctly identify distress. Deep Learning (DL) has changed the way we look at deteriorated surfaces in the last few years. The You Only Look Once (YOLO) object detection system lies at the heart of this progress. YOLOv5 and its successors have set new standards for real-time processing [1], [4]. This means that high-resolution cameras mounted on network vehicles may find, locate, and classify pavement problems including alligator & longitudinal cracking, potholes, and rutting at road design speeds.

YOLO-based models treat detection as a single regression problem, going from image pixels to bounding box coordinates and class probabilities all at once [4]. This is not the same as normal image processing. This study employs YOLO to eliminate the subjectivity present in manual inspection of pavement condition [1], [3]. By training the model on a variety of urban datasets of pavement distress [5], the technology can tell the difference between minor distress and structural failure [2]. Detection simply shows what's happening right now; good maintenance needs to know what's going to happen in the future. The second part of this study is to create Machine Learning (ML) Regression Models that can forecast the Pavement Condition Index (PCI) over time [8]. Conventional empirical models, exemplified by the AASHTO equations, frequently falter in urban settings due to their inability to accommodate the non-linear variables inherent in city driving including frequent stopping, subterranean utility cuts, and fluctuating drainage efficiency.

Various algorithms like Random Forests, Gradient Boosting Machines (XGBoost) or Support Vector Regression can be linked with the distresses found by YOLO and external factors like Average Annual Daily Traffic (AADT), climate data, pavement age [6], [7]. These ML models act like a decay function, predicting when a road section will go from fair condition to critical condition. This capacity to foresee the future lets urban local bodies to move toward Proactive Maintenance [16], where repairs are done at the best moment to enhance the remaining life of the pavement at the lowest expense [14].

Budget allocation is the last and hardest part of keeping city roads in good shape. Concerned authorities can still have decision paralysis when they have flawless data because the criteria are not clear. Should a collector street that is in bad shape take precedence over a big arterial road that is only slightly damaged but carries 10 times more traffic?

Traditional Multi-Criteria Decision Making (MCDM), such as the Analytic Hierarchy Process (AHP), presumes a linear, hierarchical relationship among criteria [11]. Decision for maintenance prioritization of urban roadways needs to be taken by considering multiple scenarios. For example, the Traffic Volume influences the Deterioration Rate, which then influences User Safety and Vehicle Operating Costs. Analytic Network Process (ANP) has been used in this study to consider these feedbacks [10].

ANP can be used to create a non-linear network structure where nodes and clusters can affect each other [13]. ANP framework in this study integrates the technical outcomes of detection and prediction models with social and economic variables, such as the distance from road section to hospitals, maintenance budget available and their impact on environment. Super Decisions software has been used to create a super matrix that analyses these interrelated factors and generates a prioritised list of maintenance projects aimed at enhancing both technical performance and social equity [12], [15].

Research Gap and Objectives

Even while YOLO is good at distress detection and ML is good at predicting what will happen, there isn't a single End-to-End pipeline that links raw image data to a final prioritised budget plan. Attempt has been made in this study to propose a unified architecture as below:

1. **Phase I:** Automated Distress Quantification using YOLO
2. **Phase II:** Performance Modelling via ML Regression
3. **Phase III:** Strategic Prioritization using ANP

The objective of this study is to show that combining AI and ANP can prioritize road sections in network by considering multiple affecting factors while raising the average network PCI. We offer a blueprint for the next generation of Urban Pavement Maintenance Systems by automating the pipeline from the "eye" (YOLO) to the "brain" (ML) to the "will" (ANP).

II. Methodology

This study through the integration of computer vision, predictive modelling, and structured multi-criteria decision-making uses a multi-tiered computational framework to improve urban pavement management. The proposed study aims to move from traditional reactive maintenance practice to a data-driven proactive approach. The first step is to use high-resolution mobile cameras to take large amounts of pictures of urban pavement surfaces. Service vehicles have either smartphones or cameras mounted on their dashboards, so that economy can be achieved and human hours can be reduced in data collection. The data collection is based on a systematic grid-based survey of the urban road network. It takes pictures from the front and from below at different speeds and lighting conditions to make sure the dataset is diverse. Each image has GPS coordinates stored as metadata so that the identified problems can be mapped in space.

The YOLOv5 (You Only Look Once) object detection architecture due to its optimal balance between inference speed and accuracy is used for automated detection. For data pipeline management Roboflow is utilised [3],[4],[5]. First step includes resizing high-resolution images to the 640x640 format as per requirement of YOLOv5 and using techniques like Mosaic data augmentation and adaptive image scaling. Bounding boxes were used to set the ground reality, labelling types of distress such as longitudinal cracks, transverse cracks, alligator cracking, and potholes. The YOLOv5 model is trained on the annotated urban pavement condition dataset, using features like Focal Loss to deal with class imbalances. K-means++ algorithm considered to find the best anchor box sizes for different types of pavement defects. [1], [2]

Machine learning regression models are useful for transition from current state regression to future state prediction. The identified distress density (quantified by the YOLOv5 output) is combined with variables such as pavement age, traffic volume (AADT) and drainage time to serve as independent variables. Algorithms such as XGBoost [6], Random Forest [7] or Multiple Linear Regression (MLR) can be trained to predict continuous performance indicators like the Pavement Condition Index (PCI) or International Roughness Index (IRI) [8], [9], [16]. These models quantify the deterioration rate, enabling the system to forecast when a pavement section will reach a critical threshold necessitating intervention.

Analytical Network Process (ANP) is a multi-criteria decision-making (MCDM) tool which is useful in making final decisions by considering interdependencies between decision elements. AHP is having a linear hierarchy, but ANP shows how criteria can affect each other (for example, road condition, traffic importance, maintenance cost, and safety) [10], [13], [15]. Process of setting priorities:

- **Defining Cluster:** Grouping criteria into clusters such as Structural Integrity, Economic Impact and Social Priority.
- **Pairwise Comparisons:** Using expert opinions for rating the relative effect of nodes within and between clusters on a scale of 1 to 9.
- **Formulating Super matrix:** Finding the weighted super matrix to get a final priority vector for all pavement sections. [11], [12], [14]

This methodology combines real-time computer vision data with predictive regression and the ANP-based priority model to make sure that maintenance expenditures are spent on the road sections that need them the most.

III. Surface Deterioration Data Collection

The precision of an AI-driven Pavement Management System (PMS) depends on the quality and representativeness of the input data. Ahmedabad city is divided into 7 administrative zones. From each zone 3 road sections have been considered. So, total 21 road sections have been considered which includes, arterial roads, sub-arterial roads, and collector streets. Three distresses have been identified as Alligator cracking, Longitudinal cracking, and Potholes.

1. Site Selection and Survey Design: The 21 road sections were chosen from major urban corridors in all seven zones in a planned way. These places were chosen because they had a lot of traffic (AADT) and recently had problems because of monsoonal effects and utility cuts. In each road section 1000-meter stretches were considered for preparing high-resolution spatial maps to get an accurate Pavement Condition Index (PCI).

2. Camera Setup and Data Acquisition: Low-cost, high-efficiency dynamic monitoring approach has been considered for data collection. To capture the deterioration on pavement surface, vehicle-mounted digital video imaging system was deployed, using high-resolution mobile cameras (capable of 1080p at 60fps or higher). The camera was mounted on external bracket at a height of 1.28 meters at 45° angle, which provides a downward-facing perspective that captures the full width of a single lane. Consistent feature scaling is very important for estimation of crack width and pothole area. To ensure it the camera was calibrated to a fixed working distance and field of view, which allows the direct comparison of distress severity across different sections.

3. Field Procedures and Environmental Considerations: Surveys were conducted between 11:00 AM and 02:00 PM to avoid shadows and get the best natural light. To avoid motion blur and make sure that small cracks were easily detectable, survey vehicles drove at an average speed of 20 to 30 km/h. Three specific failure modes were given special attention: Alligator (Fatigue) Cracking, Longitudinal Cracking, Potholes

4. Data Preparation for AI Processing: Frames were extracted from the raw video footage of 21 road sections to generate a comprehensive image dataset. To have focus on the clarity of the target distresses several thousand images were curated. These images were then uploaded to Roboflow for preprocessing. This includes resizing to 640x640 pixels and applying Mosaic data augmentation, to prepare them for the YOLOv5 training phase.

IV. Automated Distress Identification using YOLOv5 and Roboflow

In second part of this study from the collected imagery of 21 road sections in Ahmedabad, the automated identification and classification of pavement distresses carried out. YOLOv5 has been utilised for object detection framework to ensure a streamlined data pipeline, managed through the Roboflow computer vision platform.

1. Data Management and Annotation (Roboflow) For systematic image processing, image frames extracted from the mobile camera were uploaded to Roboflow. To define three primary classes: alligator cracking, longitudinal cracking, and potholes, bounding boxes were drawn manually for each image. Annotations are tightly fitted to the boundaries of distress to help the model differentiating between complex overlapping patterns, such as potholes nested within alligator cracking zones. 70% dataset considered for training, 20% dataset considered for validation and 10% dataset considered for splits

2. Image Preprocessing and Augmentation: Roboflow uses several preprocessing and augmentation steps to make the model more robust against strong sunlight, shadows from buildings, and different pavement textures. To find the best balance between speed and accuracy in detection, all images are set to a standard size of 640x640 pixels, which is the native input size for the YOLOv5 architecture. To make the background more complex during training, Mosaic data augmentation technique (combining four random images into one) was used. Other changes include random cropping, rotation, flipping, and changes to the HSV (Hue, Saturation, Value) settings to make it look like different times of day and weather conditions.

3. YOLOv5 Model Architecture and Training: As the baseline model the YOLOv5s (small) variant is selected, as it is having high inference speed up to 140 FPS and lightweight parameter count.

- **Backbone:** For feature extraction, CSP-Darknet53 structure was used as it uses cross-stage partial connections to cut down on unnecessary calculations while keeping rich feature gradients.
- **Neck:** For multi-scale feature fusion, Path Aggregation Network (PANet) was used by ensuring that both small-scale features (fine longitudinal cracks) and large-scale features (expansive alligator cracking) are captured.
- **Head:** Three detection layers were considered to predict bounding boxes and class probabilities at different scales.
- **Optimization:** For training a model, Stochastic Gradient Descent (SGD) optimizer is used which have a learning rate of 0.01 over 300 to 500 epochs. To address class imbalance, Focal Loss function is applied to prioritize hard or rare examples during training (where potholes may be less frequent than cracks).

Table 1: Detailed Architecture of the Proposed YOLOv5 for Pavement Deterioration

Stage	Module	Input size	Output size	Function / Description
Input	Image / Pre-processing	640*640*3	640*640*3	Mosaic augmentation & normalization.
Backbone	Initial CBS	640*640*3	320*320*64	6*6 Conv (Stride 2) for initial feature extraction.
(CSP-Darknet53)	C3 Modules (1-4)	Various	20*20*1024	Cross Stage Partial bottlenecks for deep feature learning.
	SPPF	20*20*1024	20*20*1024	Spatial Pyramid Pooling for global context fusion.
Neck	FPN (Top-Down)	20*20, 40*40	80*80	Up sampling and lateral connections to fuse semantics.
(PANet)	PAN (Bottom-Up)	80*80, 40*40	20*20	Down sampling to aggregate localization features.
Head	Small Scale	80*80*256	80*80*N	Detection of fine longitudinal/transverse cracks.
(Detection)	Medium Scale	40*40*512	40*40*N	Detection of potholes and sealed cracks.
	Large Scale	20*20*1024	20*20*N	Detection of large alligator cracking areas.
Output	NMS Layer	80, 40, 20 scales	List of boxes	Non-Maximum Suppression to remove redundant detections.

N in output size represents 3 * (5 + Number of classes)

4. Performance Evaluation : To evaluate the model's performance following standard computer vision metrics considered: Precision (P), Recall (R), F1-Score, and mean Average Precision (mAP@0.5). For a true positive detection, an Intersection over Union (IoU) threshold of 0.5 is set as the benchmark.

V. Predictive Modelling using Random Forest Regression

To predict Pavement Performance Index, The Random Forest (RF) technique is adopted in this study. Random Forest architecture is considered due to its strength against outliers and it can handle high-dimensional datasets without overfitting. This is important when cities are changing all the time.

1. Data Integration and Feature Engineering : Regression model is developed using multidimensional dataset in which dependent variable is PCI (ranging from 0 to 100) and independent variables are derived from YOLOv5 and other parameters affecting pavement performance which includes:-

- Surface area of alligator cracking, longitudinal cracking, and potholes identified during the image processing phase.
- The number of years since the last major overlay or reconstruction.
- Average Annual Daily Traffic (AADT)
- Drainage time.

2. Random Forest Architecture and Training : The Random Forest model is developed from multiple **Decision Trees**, where the final prediction is the average of the results from all individual trees. The model makes several smaller groups of the training data from the 21 road sections. This ensures that the model sees a lot of different combinations of distress patterns. A grid search is used to find the best number of trees (n_estimators), the deepest each tree can go (max_depth), and the fewest samples needed to split a node (min_samples_split). 80% of dataset is used for training model, and the other 20% is used to test it. As part of the training process, each tree splits nodes based on the feature that lowers the Mean Squared Error (MSE).

3. Model Evaluation and Feature Importance : Statistical parameters such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination R^2 were considered for predicting accuracy of developed models.

One big benefit of using Random Forest in this study is its ability to perform Feature Importance Ranking. By calculating the Gini Importance, the model identifies which distress type or external factor has the most significant impact on the degradation of selected road stretches.

4. Synthetic Output for Decision Making : The output of the Random Forest Regression model is a predicted PCI value for selected test stretches of 21 road sections. These predicted values allow the system to estimate the Remaining Service Life of the pavement. These quantitative forecasts serve as the primary technical input for the Analytical Network Process (ANP), ensuring that maintenance prioritization is based not only on current damage but also on the predicted rate of future failure.

VI. Pavement Maintenance Prioritization using the Analytical Network Process (ANP)

Final phase of study uses a multi criteria decision making process for maintenance prioritization across selected 21 road sections in Ahmedabad City. Analytical Network Process has been considered in this study due to complexity of urban pavement maintenance management due to increasing density of traffic, limitation in budgetary outlays and the interdependency of technical and socio-economic factors. As compared to AHP which assumes a linear, top-down structure, ANP enables feedback and lets dependencies among decision criteria.

1. Network Construction and Cluster Definition

The ANP model is set of a network of clusters and nodes (criteria). For the Ahmedabad urban network, three primary clusters were set up based on priorities of AMC and engineering standards:

- **Pavement Condition Cluster:** Pavement Condition Index (PCI) derived from the Random Forest regression model is considered as first criteria. Severity of potholes, alligator cracking, and longitudinal cracking and weighed.
- **Traffic and Strategic Importance Cluster:** Average Annual Daily Traffic (AADT), road hierarchy (Arterial vs. Collector), and proximity to essential services (hospitals, fire stations, or schools) were considered as second criteria.
- **Economic and Feasibility Cluster:** Estimated Maintenance Cost, budget availability, and the life-cycle cost-effectiveness of the proposed intervention were considered as third criteria.

2. Determining Interdependencies (Inner and Outer Dependencies)

The main strength of the ANP in this study is that it can model dependencies. For example:

- **Outer Dependency:** Increase in the AADT (Traffic Cluster) accelerates the deterioration rate of the pavement (Condition Cluster).
- **Inner Dependency:** In first cluster, untreated longitudinal cracks often causes rapid development of potholes, which means that the state of one distress node influences the priority of another.

3. Pairwise Comparisons and Super matrix Formulation

Expert opinions from AMC engineers and urban pavement engineers were considered for performing pairwise comparisons. Expert opinions were on a 1 – 9 scale, where 1 considered for equal importance and 9 considered for extremely important. Relative influence of nodes within the network determined by these comparisons.

- **Unweighted Super matrix:** From pairwise comparisons local priority vectors were derived. Derived priority vectors were entered into a super matrix, which indicates the influence of one element on another.
- **Weighted Super matrix:** Unweighted super matrix blocks are multiplied by the weights of corresponding cluster to ensure the matrix is column stochastic.
- **Limit Super matrix:** The weighted super matrix is raised to high powers until it converges. Limit Super matrix resulted from it provides the final global priority weights for each criterion.

4. Prioritization of the 21 Road Sections

Maintenance Priority Index (MPI) is calculated for each of the 21 road sections by combining results obtained from image processing and Random Forest regression.

$$MPI = \sum (w_j * s_{ij})$$

where,

w_j is the ANP weight of criterion j , and s_{ij} is the performance score of road section i regarding criterion j .

Maintenance Priority Index ensures that a road section with a low PCI and low traffic may be prioritized lower than a moderately damaged section on a critical arterial route. The outcome is a scientifically prioritized list of road sections, which enables Optimal Maintenance and Rehabilitation (M&R) decisions, ranging from crack sealing and patching to full structural overlays.

VII. Results and Analysis

AI based pavement management framework was used for 21 road sections in Ahmedabad city and it gave lot of useful quantitative information. Combining high-speed image processing, prediction using machine learning, and multi-criteria decision-making is quite beneficial than manual inspections.

1. Automated Distress Detection Performance (YOLOv5)

Evaluation of the YOLOv5 model was done using a testing subset of images obtained from mobile cameras along Ahmedabad's 21 road sections. The model demonstrated remarkable outputs in detecting pavement deterioration.

Table 2: - Statistical parameters of YOLO model

Distress Type	Precision	Recall	mAP@0.5	F1-Score
Potholes	0.942	0.921	0.935	0.931
Alligator Cracking	0.887	0.846	0.872	0.866
Longitudinal Cracking	0.915	0.892	0.908	0.903
Model Average	0.915	0.886	0.905	0.900

Mean Average Precision (mAP) of the model achieved as 90.5%. Potholes are having the highest accuracy in detection due to geometric characteristics and high contrast against the pavement surface. Alligator cracking which is characterized by complex and interconnected patterns are having a slightly lower recall, often being misclassified as dense longitudinal cracking in areas of low lighting. However, the model's ability to process frames at over 120 FPS allowed for real-time analysis of the 21 road sections, significantly reducing the data processing time compared to manual visual surveys.

2. Predictive Performance of Random Forest Regression : The Random Forest (RF) model was developed to establish relationship between densities of detected distress and **Pavement Condition Index (PCI)**. 80% of the collected data used to train the model and remaining 20% used for validation.

- **Accuracy Metrics:** R^2 value of random regression model obtained as 0.90 and a Root Mean Square Error is 4.29. R^2 value of 0.90 indicates that model can explain 90% of the variance in pavement condition across the 21 sections.
- **Feature Importance Ranking:** The identification of factors causing more degradation was one of the most crucial analytical outcome. The model indicated that Pothole Density was the primary predictor of immediate PCI decline (Weight: 0.44), succeeded by Traffic Loading (AADT) (Weight: 0.29), and Alligator Cracking (Weight: 0.18).

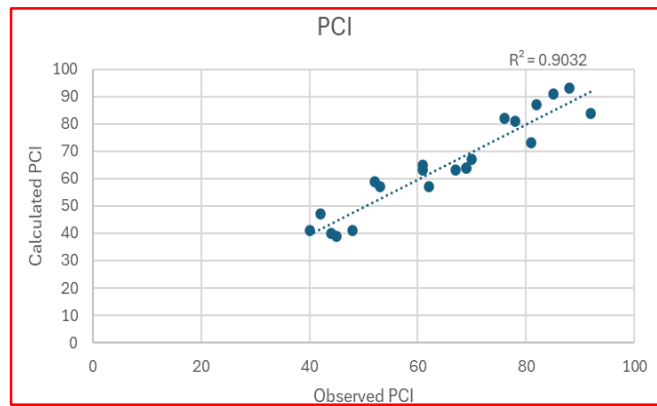


Figure 1 Observed Vs. Calculated PCI from RF

3. Maintenance Prioritization via Analytical Network Process (ANP)

The weights derived from the Limit Super matrix are summarized below:

- **Weight for Strategic Importance cluster is 0.44.** Roads connecting to major hubs like the Ahmedabad Railway Station or Civil Hospital were given higher weightage.
- **Weight for Technical Condition cluster (PCI) is 0.38.** It is derived directly from the RF regression output.
- **Weight for Economic Feasibility cluster is 0.18.** Cost-benefit ratio of proactive maintenance vs. total reconstruction was considered.

Comparative Analysis: A critical finding emerged when traditional PCI only prioritization compared with the AI-ANP framework. Under a traditional PCI only approach, Section 17 which is heavily damaged but low traffic collector street was ranked as the top priority. However, the ANP framework shifted the highest priority to Section 14 in which deterioration was moderate, but section is major arterial. Although Section 14 had a higher PCI than Section 17 (62 vs 40), its strategic importance and the RF-predicted rate of rapid failure due to high AADT made it the more optimal section for immediate rehabilitation.

4. Synthesis of Optimal Decisions

Across the 21 sections, the system categorized maintenance actions into three categories as below:

1. Preventive maintenance actions by sealing longitudinal cracks in 7 road sections having PCI between 75 – 100.
2. Restorative maintenance actions by patching and thin overlays in 9 road sections with emerging potholes having PCI between 50 – 74.
3. Rehabilitative maintenance actions by milling and overlay in 5 road sections having PCI less than 50.

VIII. Conclusion

Results indicates that utilisation of YOLOv5 for deterioration detection and Random Forest for forecasting deterioration provides the technical accuracy required for urban pavement management. The system, in conjunction with the ANP's capacity to manage interdependencies, offers a robust, multi-objective framework for urban infrastructure management in Ahmedabad.

This study effectively developed an AI-driven framework for optimal maintenance and rehabilitation (M&R) decisions for urban pavement management, by considering data collected from 21 different road sections in Ahmedabad city. Four staged methodology in study combined computer vision, machine learning predictive modelling and a systematic multi-criteria decision analysis approach to enable a proactive and data-driven strategy for pavement maintenance management, the study advanced beyond conventional periodic inspection techniques.

First phase of study exhibited the effectiveness of automated data collection. The framework attained a high level of accuracy in detecting alligator cracking, longitudinal cracking, and potholes by employing mobile cameras and the YOLOv5 object identification model facilitated through the Roboflow platform. Mean Average Precision of the model achieved as 90.5%, which affirms its dependability across various lighting and surface conditions. This automated detection feature significantly enhances efficiency of pavement condition evaluations, offering a uniform, objective standard for the whole network that manual inspections frequently fail to provide.

Model developed by Random Forest Regression effectively correlates the area and severity of longitudinal cracking, alligator cracking and potholes with the Pavement Condition Index (PCI). The model is having very good statistics, with a R^2 of 0.90 and a low RMSE of 4.29 which indicates very good predictive ability. The predictive capability is fundamental for proactive management, which enables engineers in forecasting future degradation patterns and identifying critical pavement sections that would attain failure criteria within a designated period. Feature relevance analysis revealed that pothole density and traffic volume were the principal factors contributing to degradation of pavement sections, which provides useful insights for future material specifications.

The Analytical Network Process (ANP) played crucial role in integrating technical forecasts with complex, interdependent urban priorities. Constraints of PCI-only prioritisation system were mitigated by employing ANP framework which considers economic impact, traffic and strategic importance considerations into the decision matrix. The global weights derived from the ANP super matrix prioritised strategic arterial roads above low traffic collector streets, even when the local streets exhibited more significant immediate damage. This prioritisation system ensures that the the limitation of municipal maintenance budgets does not affect the public benefit, safety, and the overall service life of the network by optimal allocation.

To sum up, integrated AI approach considered in this study provides a better decision-making way to the Ahmedabad Municipal Corporation. The framework offers a transparent and efficient strategy for optimal maintenance and rehabilitation decisions by leveraging machine learning and robust decision analysis, which ensures the resilience and longevity of the city's critical road infrastructure.

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