



Midocean University

Faculty of Management

Project Management Department

**Hybrid Intelligent Framework for Pavement and Bridge Condition
Assessment and Maintenance Prioritization in Abu Dhabi**

Prepare by

Ahmed Mubark Mohammed Ali

Supervised by

D.Faez Ali Girad

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1. Introduction

Infrastructure systems—particularly road and bridge networks—represent the backbone of modern urban development. They facilitate economic growth, support social mobility, and ensure the continuity of transportation activities. In rapidly developing regions such as the Emirate of Abu Dhabi, the demand for resilient, efficient, and sustainable infrastructure has

increased significantly due to accelerated urban expansion, rising traffic volumes, and the strategic importance of mobility within the region.

However, Abu Dhabi's infrastructure faces unique challenges. The Emirate is characterized by extreme climatic conditions, including high temperatures, humidity, and exposure to coastal salinity. These environmental factors accelerate the deterioration of pavements and bridge structures. Combined with heavy traffic loads and natural material degradation, these conditions create a pressing need for advanced, reliable, and scalable assessment systems.

Traditional inspection methods—such as visual surveys, IRI measurements, and FWD testing—remain widely used but suffer from several limitations. They are labour-intensive, time-consuming, costly, and prone to human subjectivity. Moreover, they are not designed to handle the large volumes of data generated by modern infrastructure monitoring systems. As a result, decision-makers often lack timely, accurate, and integrated information to support maintenance planning.

Recent advancements in artificial intelligence (AI), including machine learning (ML), deep learning (DL), and computer vision (CV), offer transformative opportunities for infrastructure assessment. These technologies can analyse multi-source datasets, detect patterns, predict deterioration, and automate condition evaluation with high accuracy. Despite these advancements, there remains a significant gap: **no existing framework integrates AI-based pavement and bridge assessment into a unified maintenance prioritization system tailored to Abu Dhabi's environment.**

This research addresses this gap by proposing a **hybrid intelligent framework** that combines ML-based pavement assessment, CV-based bridge evaluation, and a multi-criteria prioritization algorithm. The framework aims to support government agencies in making data-driven, cost-effective, and sustainable maintenance decisions.

1.1 Background of the Study

The Emirate of Abu Dhabi manages an extensive network of roads and bridges that serve as critical infrastructure assets. Over the past decade, the government has invested heavily in expanding and modernizing transportation systems. However, maintaining these assets in optimal condition requires continuous monitoring, timely interventions, and efficient allocation of maintenance resources.

1.2 Challenges in Pavement Assessment

Pavement deterioration in Abu Dhabi is influenced by:

- Extreme heat causing asphalt softening and rutting
- Heavy traffic loads accelerating fatigue cracking
- Environmental factors such as sand intrusion and UV exposure

- Variations in material performance (e.g., 40/50 vs. 82/22 bitumen)

Traditional pavement assessment tools—such as IRI, FWD, and PCI—provide valuable insights but are limited when used independently. They do not fully capture the complex interactions between traffic, climate, and material properties.

1.3 Challenges in Bridge Assessment

Bridge structures face additional challenges:

- Chloride-induced corrosion in coastal areas
- Thermal expansion and contraction
- Structural fatigue due to heavy vehicle loads
- Human subjectivity in visual inspections

Deep learning models, particularly CNNs, have demonstrated superior performance in detecting cracks and classifying their severity. However, these models are rarely integrated into broader asset management systems.

1.4 Need for an Integrated Framework

Current practices in Abu Dhabi treat pavements and bridges as separate asset classes, each evaluated using different tools and criteria. This fragmentation leads to:

- Inconsistent assessment results
- Difficulty in comparing maintenance needs across asset types
- Inefficient budget allocation
- Lack of unified prioritization

A hybrid intelligent framework that integrates both asset types into a unified system can significantly enhance decision-making and long-term planning.

2. Problem Statement

Despite the availability of extensive infrastructure datasets and the rapid advancement of artificial intelligence technologies, Abu Dhabi still lacks a unified, intelligent framework that integrates pavement and bridge condition assessment with multi-criteria maintenance prioritization. Current evaluation practices remain fragmented, relying heavily on manual inspection and traditional single-indicator approaches that fail to capture the complexity of material behaviour and distress mechanisms under the region's harsh climatic conditions. Pavement surfaces across Abu Dhabi exhibit a wide range of distresses, including longitudinal and transverse cracking, joint cracks, potholes, depressions, rutting, bleeding, and other surface defects often associated with very loose to loose formation materials and

aging asphalt mixes. Similarly, bridge structures suffer from cracks, spalling, corrosion, and expansion joint damage, which compromise structural integrity and serviceability. These issues are exacerbated by high temperatures, heavy traffic loads, and coastal exposure to chlorides. There is currently no AI-driven, unified framework capable of integrating pavement and bridge condition assessment with multi-criteria maintenance prioritization tailored to Abu Dhabi's climatic and operational environment. Artificial intelligence—through machine learning (e.g., XGBoost) and computer vision (e.g., CNN)—can automatically detect, classify, and quantify various types of pavement and bridge defects, while simultaneously analysing material performance to recommend alternative, more durable materials. By learning from historical datasets and multisource inspection data, AI can identify correlations between distress types and material properties, enabling the selection of optimized asphalt mixtures, modified binders, and concrete compositions that outperform traditional raw materials in hot and coastal conditions.

This research addresses the urgent need for a hybrid AI framework that not only enhances defect detection and condition assessment but also supports data-driven decision-making for material selection and maintenance prioritization across Abu Dhabi's road and bridge network.

3. Aim and Objectives

3.1 Aim of the Study

The primary aim of this research is to develop a hybrid intelligent framework that integrates machine learning and computer vision techniques to assess pavement and bridge conditions across Abu Dhabi's road networks. The framework will also incorporate a multi-criteria maintenance prioritization model to support data-driven decision-making and optimize resource allocation.

3.2 Specific Objectives

To achieve this aim, the study pursues the following objectives:

1. **Data Acquisition and Analysis:** Collect and analyse pavement and bridge datasets, including IRI, FWD, distress data, inspection images, traffic volumes, and environmental factors.
2. **Pavement Condition Modelling:** Develop a machine learning model (XGBoost) capable of predicting pavement condition indices and identifying key distress patterns.
3. **Bridge Condition Modelling:** Develop a deep learning model (CNN/ResNet50) for automated crack detection and severity classification using bridge inspection imagery.
4. **Unified Condition Score (CS):** Integrate pavement and bridge assessment outputs into a single, normalized condition score.

5. **Maintenance Prioritization Score (MPS):** Develop a multi-criteria decision-making model that incorporates condition, traffic importance, risk, and cost.
6. **Framework Evaluation:** Compare the performance of the proposed framework with traditional assessment and prioritization methods.

4. Research Questions

This study seeks to answer the following key questions:

- 1- How can artificial intelligence improve the accuracy and efficiency of pavement condition assessment in Abu Dhabi, particularly in detecting and classifying asphalt distresses such as longitudinal and transverse cracks, joint failures, potholes, depressions, rutting, bleeding, and surface deterioration associated with loose or weak subgrade materials?
- 2- Can computer vision models outperform traditional visual inspection in identifying and quantifying bridge defects such as concrete cracking, spalling, corrosion, and expansion joint damage, while providing automated severity classification and spatial mapping for maintenance planning?
- 3- How can the outputs of AI-based pavement and bridge assessment models be integrated into a unified maintenance prioritization system that accounts for multi-criteria factors including distress severity, traffic importance, material performance, and environmental exposure?
- 4- What is the comparative effectiveness of the proposed hybrid intelligent framework—combining XGBoost, CNN, and MPS—in detecting complex pavement and bridge defects and recommending alternative, more durable materials compared to traditional inspection and maintenance methods used by local agencies in Abu Dhabi?

5. Research Hypotheses

The study is grounded in the following hypotheses:

H1:

Machine learning models (e.g., XGBoost) significantly improve PCI prediction accuracy compared to traditional single-indicator methods such as IRI or FWD.

H2:

CNN-based models (e.g., ResNet50) provide superior crack detection and severity classification compared to manual visual inspection.

H3:

A unified condition score integrating pavement and bridge outputs provides a more comprehensive and accurate representation of infrastructure condition.

H4:

A multi-criteria prioritization algorithm (MPS) yields more objective and accurate maintenance rankings than traditional PCI/BCI-based methods.

H5:

Roads constructed with modified bitumen (82/22) perform better under Abu Dhabi's hot climate than those using 40/50 bitumen.

H6:

Bridges located near coastal areas exhibit higher crack severity due to chloride exposure compared to inland bridges.

H7:

The proposed intelligent framework is practical, implementable, and enhances maintenance decision-making for government agencies.

6. Significance of the Study

6.1 Practical Significance

This study provides a practical, government-ready framework that can significantly enhance infrastructure management in Abu Dhabi. Its practical contributions include:

- **Improved Assessment Accuracy:** AI models reduce subjectivity and enhance consistency in pavement and bridge evaluations.
- **Reduced Inspection Costs:** Automated assessment minimizes the need for extensive manual surveys.
- **Optimized Maintenance Planning:** The MPS model supports data-driven prioritization, improving budget allocation.
- **Suitability for Harsh Climates:** The framework is tailored to Abu Dhabi's extreme heat, humidity, and coastal conditions.
- **Integration with GIS:** Outputs can be visualized spatially, enabling better decision-making.

6.2 Scientific Significance

The study contributes to the academic literature by:

- Integrating machine learning and computer vision within a unified infrastructure assessment framework.
- Addressing a major gap in AI applications for hot-climate environments.

- Providing a theoretical integration of ML, MCDM, and asset management principles.
- Offering a replicable methodology for other regions with similar environmental challenges.

7. Literature Review

This section provides a deeper overview of the literature on pavement and bridge assessment, highlighting the evolution from traditional methods to AI-based approaches.

7.1 Pavement Condition Assessment

Traditional Approaches

Traditional pavement assessment relies on:

- **IRI:** Measures surface roughness but does not capture structural condition.
- **FWD:** Provides structural capacity but requires specialized equipment.
- **PCI:** Based on visual distress surveys, subjective and labour-intensive.

These methods are limited when used independently and are not scalable for large networks.

AI-Based Approaches

Recent studies demonstrate that:

- **XGBoost** improves PCI prediction accuracy.
- **Random Forest and ANN** models capture nonlinear relationships between distress, traffic, and climate.
- **Multi-source data integration** enhances model robustness.

7.1.1 Bridge Condition Assessment

Traditional Approaches

Visual inspection remains the primary method but suffers from:

- Human subjectivity
- Inconsistent evaluations
- Limited ability to detect fine cracks

AI-Based Approaches

Deep learning models such as:

- **CNN**

- **ResNet**
- **YOLO**

have achieved high accuracy in crack detection and severity classification. SHM-based models (1D-CNN, LSTM) detect early structural damage using vibration data.

7.1.2 Infrastructure Asset Management

Infrastructure asset management is a systematic process that involves the planning, operation, maintenance, and rehabilitation of physical assets to ensure optimal performance throughout their lifecycle. Traditional asset management approaches rely heavily on engineering judgment, periodic inspections, and budget-driven decision-making. However, these approaches often lack the analytical depth required to handle large datasets or incorporate multi-dimensional criteria such as risk, traffic importance, and environmental exposure.

7.1.3 Traditional Asset Management Approaches

Traditional methods typically use:

- **Pavement Condition Index (PCI)** for pavements
- **Bridge Condition Index (BCI)** for bridges
- **Annual maintenance budgets**
- **Inspector-based evaluations**

While these methods provide a baseline understanding of asset condition, they suffer from:

- Limited scalability
- High subjectivity
- Inability to integrate multi-source data
- Lack of predictive capabilities

7.1.4 Modern Asset Management Approaches

Recent studies emphasize the importance of integrating:

- **Artificial Intelligence (AI)**
- **Geographic Information Systems (GIS)**
- **Multi-Criteria Decision-Making (MCDM)**
- **Predictive analytics**

These modern approaches enable:

- **Data-driven decision-making**

- Long-term maintenance planning
- Improved resource allocation
- Enhanced transparency and accountability

However, most existing studies focus on either pavements or bridges, not both, and very few are tailored to hot-climate environments like Abu Dhabi.

7.1.5 Maintenance Prioritization Models

Maintenance prioritization is a critical component of infrastructure management, ensuring that limited resources are allocated to assets with the highest need or risk. Traditional prioritization methods often rely on single indicators such as PCI or BCI, which do not capture the full complexity of infrastructure performance.

7.1.6 Traditional Prioritization Methods

Common methods include:

- **Analytic Hierarchy Process (AHP)**
- **TOPSIS**
- **Weighted scoring systems**

These methods provide structured decision-making but lack integration with AI-based assessment outputs.

7.2 Limitations of Traditional Methods

Traditional prioritization approaches:

- Do not incorporate multi-source data
- Do not integrate AI-generated condition scores
- Do not consider traffic importance, risk, or cost simultaneously
- Are not optimized for large-scale networks

7.3 Need for AI-Integrated Prioritization

An AI-integrated prioritization model can:

- Improve accuracy
- Reduce subjectivity
- Enhance scalability
- Support real-time decision-making

This study addresses this gap by developing a **Maintenance Prioritization Score (MPS)** that integrates condition, traffic, risk, and cost into a unified ranking system.

8. Comparative Analysis of Previous Studies

A detailed comparative analysis reveals significant differences in methodologies, data types, and objectives across previous studies. The following sections summarize the key findings.

8.1 Similarities Across Studies

1. **AI improves assessment accuracy** Most studies agree that machine learning and deep learning outperform traditional methods.
2. **Multi-source data enhances model robustness** Studies highlight the importance of integrating IRI, FWD, distress, and imagery.
3. **CNNs dominate crack detection research** CNN, ResNet, and YOLO are widely used for bridge crack detection.
4. **Need to reduce cost and time** AI-based methods offer faster and more scalable alternatives to manual inspection.

8.2 Differences Across Studies

1. **Variation in data types**
 - Some use only surface distress
 - Others use IRI or FWD
 - Bridge studies use imagery or SHM data
 - Very few combine multiple data sources
2. **Differences in application environments** Most studies are conducted in the US, China, or Korea. Very few address hot-climate environments like the UAE.
3. **Differences in objectives**
 - Some focus on prediction
 - Others on crack detection
 - Few integrate results into prioritization models
4. **Differences in algorithms**
 - Pavements: RF, SVM, XGBoost, ANN
 - Bridges: CNN, ResNet, YOLO, LSTM
5. **Differences in scale**

- Some studies use small datasets
- Few use large-scale real-world data
- Very few propose government-ready frameworks

8.3 Research Gaps Identified

Based on the comparative analysis, the following gaps are evident:

1. **No unified framework combining pavement and bridge assessment**
2. **Lack of studies tailored to Gulf-region hot climates**
3. **Limited integration of multi-source pavement data**
4. **No AI-integrated maintenance prioritization models**
5. **Absence of GIS-based critical asset mapping**
6. **Lack of practical, implementable frameworks for government agencies**

These gaps justify the development of the proposed hybrid intelligent framework.

8.4 Comparative Matrix Table

Researcher & Year	Asset Type	Data Used	Algorithms	Objective	Strengths	Weaknesses	Gaps
Zhang et al., 2021	Pavement	IRI + Distress	CNN	Crack detection	High accuracy	Limited dataset	No data integration
Gopalakrishnan, 2020	Pavement	IRI	RF, SVM	Condition prediction	Strong models	Single indicator	No comprehensive framework
Nguyen et al., 2022	Pavement	IRI + FWD	XGBoost	PCI prediction	Multi-source data	No traffic data	No prioritization
Dorafshan et al., 2019	Bridge	Images	CNN	Crack detection	Excellent performance	No component-level evaluation	No holistic assessment
Cha et al., 2021	Bridge	Images	ResNet	Crack severity	High accuracy	Small dataset	No SHM integration
Abdeljaber et al., 2020	Bridge	SHM	1D-CNN	Damage detection	Vibration analysis	No imagery	No visual assessment

Ferreira et al., 2020	Pave ment	PCI	MCDM	Prioritiz ation	Clear methodolo gy	No AI	No bridge integratio n
Elbeltagi et al., 2021	Gener al assets	Mixe d data	AI + MCDM	Asset manage ment	Comprehe nsive framewor k	Not specific to pavements/b ridges	No Gulf- region focus

9.Theoretical Framework

The theoretical foundation of this research integrates three major scientific theories: **Machine Learning Theory**, **Multi-Criteria Decision-Making (MCDM) Theory**, and **Infrastructure Asset Management Theory**. Together, these theories provide a solid foundation for developing an intelligent, unified framework for pavement and bridge condition assessment and maintenance prioritization.

9.1 Machine Learning Theory

Machine Learning (ML) Theory is based on the principle that computational systems can learn from data, identify patterns, and make predictions without explicit programming. ML models are particularly effective in handling large, complex datasets and uncovering nonlinear relationships between variables.

In this study, ML Theory is applied through:

- **XGBoost**, a gradient boosting algorithm known for its high predictive accuracy and ability to handle heterogeneous datasets.
- **Feature engineering**, enabling the extraction of meaningful variables from pavement datasets (IRI, FWD, distress, traffic, climate).
- **Model training and validation**, ensuring generalization and minimizing prediction error.

ML Theory supports the development of a robust pavement condition prediction model capable of outperforming traditional single-indicator methods.

9.2 Deep Learning and Computer Vision Theory

Deep Learning (DL) extends ML by enabling models to learn hierarchical representations of data. Convolutional Neural Networks (CNNs), a core DL architecture, are particularly effective for image-based tasks such as crack detection and severity classification.

Key theoretical components include:

1. Convolutional Layers

These layers apply filters to extract spatial features from images, such as edges, textures, and crack patterns.

2. Pooling Layers

Pooling reduces spatial dimensions while preserving essential features, improving computational efficiency and generalization.

3. Activation Functions

Functions such as ReLU introduce nonlinearity, enabling the model to learn complex patterns.

4. Fully Connected Layers

These layers map extracted features to output classes, such as crack severity levels.

5. SoftMax Classification

SoftMax converts model outputs into probability distributions for multi-class classification.

In this study, CNN and ResNet50 architectures are used to analyse bridge inspection images and classify crack severity with high accuracy.

9.3 Multi-Criteria Decision-Making (MCDM) Theory

MCDM Theory provides a structured approach for evaluating alternatives based on multiple, often conflicting criteria. It assumes that each criterion can be assigned a weight reflecting its relative importance.

In this study, MCDM Theory is used to develop the **Maintenance Prioritization Score (MPS)**, which integrates:

- **Condition score (CS)**
- **Traffic importance**
- **Risk level**
- **Maintenance cost**

This enables a holistic and objective prioritization of maintenance needs across the network.

9.4 Infrastructure Asset Management Theory

Infrastructure Asset Management Theory emphasizes the systematic evaluation, maintenance, and rehabilitation of engineering assets to ensure long-term performance and cost-effectiveness.

Key principles include:

- **Lifecycle management**

- Performance monitoring
- Risk-based decision-making
- Optimization of maintenance resources

This study operationalizes these principles by integrating AI-based assessment results into a practical, government-ready framework.

9.5 Integration of Theories

The proposed framework represents the intersection of:

- **Machine Learning** for pavement condition prediction
- **Deep Learning** for bridge crack detection
- **MCDM** for maintenance prioritization
- **Asset Management** for practical implementation

This integration ensures that the framework is both scientifically rigorous and operationally relevant.

10. Conceptual Framework

The conceptual framework illustrates the flow of data and processes within the proposed hybrid intelligent system. It consists of five major components: **data inputs, AI models, unified condition scoring, maintenance prioritization, and decision-support outputs.**

10.1 Data Inputs

The framework relies on diverse datasets, including:

Pavement Data

- International Roughness Index (IRI)
- Falling Weight Deflectometer (FWD)
- Surface distress data
- Traffic volumes
- Asphalt mix type (e.g., 40/50, 82/22)
- Climate data (temperature, humidity)

Bridge Data

- Inspection images
- Crack severity ratings



- Structural component evaluations
- Environmental exposure (e.g., coastal salinity)

Supporting Data

- Maintenance cost estimates
- Risk indicators
- Geographic Information System (GIS) layers

10.2 Artificial Intelligence Models

Two primary AI models are developed:

1. XGBoost Pavement Model

- Predicts PCI or equivalent condition score
- Integrates multi-source pavement data
- Identifies key distress predictors

2. CNN/ResNet Bridge Model

- Detects cracks in bridge images
- Classifies severity levels
- Supports automated visual inspection

10.3 Unified Condition Score (CS)

Outputs from both AI models are normalized and combined into a **Unified Condition Score**, enabling cross-asset comparison between pavements and bridges.

10.4 Maintenance Prioritization Score (MPS)

The MPS integrates four criteria:

1. Condition (CS)
2. Traffic importance
3. Risk level
4. Maintenance cost

Weights are assigned using expert judgment or analytic hierarchy methods.

10.5 Framework Outputs

The final outputs include:

- A prioritized list of assets requiring maintenance
- GIS-based maps highlighting critical assets
- Decision-support dashboards for government agencies

These outputs enhance transparency, efficiency, and long-term planning.

11. Proposed Methodology

The methodology of this research is designed to ensure a systematic, strict, and scientifically valid approach to developing the hybrid intelligent framework. It consists of **seven major phases**, each contributing to the overall objective of integrating AI-based assessment with multi-criteria maintenance prioritization.

11.1 Phase 1: Data Collection

Data collection is a foundational step in this study. The research will obtain datasets from relevant government agencies in Abu Dhabi, such as the Department of Municipalities and Transport (DMT) and Abu Dhabi Mobility (ADM). The datasets include:

Pavement Data

- International Roughness Index (IRI)
- Falling Weight Deflectometer (FWD)
- Surface distress data (cracking, rutting, raveling, bleeding)
- Traffic volume and classification
- Asphalt mix type (40/50, 82/22)
- Climate data (temperature, humidity, UV index)

Bridge Data

- High-resolution inspection images
- Crack severity ratings
- Structural component evaluations (deck, girders, piers)
- Environmental exposure (coastal vs. inland)

Supporting Data

- Maintenance cost estimates
- Risk indicators (accident history, structural vulnerability)
- GIS layers (location, road hierarchy)

This phase ensures that the framework is built on **real-world, high-quality datasets** representative of Abu Dhabi's infrastructure.

11.2 Phase 2: Data Preprocessing

Raw data often contains inconsistencies, missing values, and noise. Therefore, preprocessing is essential to ensure model accuracy and reliability.

Key preprocessing steps include:

- **Data cleaning:** Removing duplicates, correcting errors, handling missing values
- **Normalization:** Scaling numerical features for ML models
- **Feature engineering:** Creating new variables such as distress severity indices
- **Image preprocessing:**
 - Resizing
 - Contrast enhancement
 - Noise reduction
 - Annotation of cracks for supervised learning

This phase ensures that the datasets are ready for machine learning and deep learning model development.

11.3 Phase 3: AI Model Development

This phase involves developing two core AI models:

1. Pavement Condition Model (XGBoost)

The XGBoost model will be trained to predict pavement condition indices using multi-source data. Key steps include:

- Splitting data into training, validation, and testing sets
- Hyperparameter tuning (learning rate, depth, estimators)
- Model evaluation using RMSE, MAE, and R^2 metrics
- Feature importance analysis to identify key predictors

2. Bridge Condition Model (CNN/ResNet50)

The deep learning model will classify crack severity in bridge images. Key steps include:

- Building a CNN or fine-tuning a pre-trained ResNet50
- Using annotated images for supervised training

- Applying data augmentation to improve generalization
- Evaluating performance using accuracy, precision, recall, and F1-score

This phase results in **two high-performance AI models** capable of automated condition assessment.

11.4 Phase 4: Unified Condition Score (CS)

The outputs of the pavement and bridge models will be normalized and integrated into a **Unified Condition Score**. This score:

- Ranges from 0 (very poor) to 100 (excellent)
- Allows cross-asset comparison
- Provides a single metric for decision-makers

Normalization techniques such as min-max scaling or z-score standardization will be applied.

11.5 Phase 5: Maintenance Prioritization Score (MPS)

The MPS is a multi-criteria decision-making model that integrates:

1. **Condition score (CS)**
2. **Traffic importance**
3. **Risk level**
4. **Maintenance cost**

Each criterion will be assigned a weight based on expert judgment or AHP analysis. The final MPS score will determine the priority ranking of each asset.

11.6 Phase 6: Framework Validation

Validation ensures that the proposed framework is reliable and practical.

Validation methods include:

- Comparing AI predictions with actual field data
- Benchmarking against traditional PCI/BCI methods
- Sensitivity analysis of MPS weights
- Expert review sessions with DMT/ADM engineers

This phase confirms the framework's accuracy, robustness, and applicability.

11.7 Phase 7: GIS Integration and Visualization

The final step involves integrating the results into a GIS platform to support decision-making.

GIS outputs include:

- Heat maps of pavement and bridge conditions
- Spatial distribution of high-risk assets
- Maintenance priority maps
- Interactive dashboards for decision-makers

This ensures that the framework is **practical, visual, and ready for government implementation.**

12. Expected Contributions

This research is expected to make significant scientific and practical contributions.

12.1 Scientific Contributions

1. Development of a unified AI-based framework for pavement and bridge assessment.
2. Integration of machine learning, deep learning, and MCDM into a single system.
3. Novel methodology tailored to hot-climate environments.
4. Contribution to the academic literature on infrastructure asset management.
5. Introduction of a Unified Condition Score applicable across asset types.

12.2 Practical Contributions

1. A government-ready maintenance prioritization tool.
2. Improved accuracy and consistency in infrastructure assessment.
3. Reduced reliance on manual inspection.
4. Enhanced budget allocation and resource optimization.
5. GIS-based visualization for strategic planning.
6. Framework scalable to other regions in the UAE and GCC.

13. Validation and Evaluation Plan

Ensuring the reliability, accuracy, and practical applicability of the proposed hybrid intelligent framework is a critical component of this research. The validation plan includes multiple layers of evaluation to confirm that the AI models and prioritization system perform effectively under real-world conditions.

13.1 Model Validation

13.1.1 Pavement Model (XGBoost) Validation

The pavement condition prediction model will be validated using:

- **Train–validation–test split** to ensure generalization
- **Performance metrics**, including:
 - Root Mean Square Error (RMSE)
 - Mean Absolute Error (MAE)
 - Coefficient of Determination (R^2)
- **Cross-validation** to reduce overfitting
- **Feature importance analysis** to verify that the model aligns with engineering expectations (e.g., rutting depth, IRI, traffic volume)

This ensures that the model is both statistically sound and engineering-relevant.

13.1.2 Bridge Model (CNN/ResNet50) Validation

The bridge crack detection model will be validated using:

- **Confusion matrix**
- **Accuracy, precision, recall, F1-score**
- **ROC curves** for multi-class severity classification
- **External validation** using images not included in the training dataset
- **Expert comparison**, where structural engineers review model outputs

This ensures that the model performs reliably across diverse bridge conditions and lighting environments.

13.2 Unified Condition Score (CS) Validation

The Unified Condition Score will be validated by:

- Comparing CS values with actual field inspection results
- Conducting **sensitivity analysis** to test the effect of normalization methods
- Ensuring that CS values correlate with known deterioration patterns
- Reviewing CS outputs with domain experts from DMT/ADM

This step ensures that the unified score is meaningful, interpretable, and aligned with engineering judgment.

13.3 Maintenance Prioritization Score (MPS) Validation

The MPS will be validated through:

- **Scenario testing**, where different weight combinations are applied
- **Expert workshops**, where engineers evaluate the prioritization results
- **Comparison with historical maintenance decisions**
- **Risk-based validation**, ensuring high-risk assets consistently rank higher

This ensures that the prioritization model is robust, objective, and practical for real-world use.

13.4 Framework-Level Validation

The entire framework will undergo:

- **Pilot testing** on a selected road and bridge network segment
- **Comparison with traditional methods** (PCI/BCI-based prioritization)
- **Stakeholder feedback sessions** with government agencies
- **GIS-based validation**, ensuring spatial accuracy of outputs

This confirms that the framework is ready for operational deployment.

13.5 GIS Integration and Decision-Support Tools

A key innovation of this research is the integration of AI-based assessment results into a Geographic Information System (GIS). This enhances visualization, decision-making, and long-term planning.

13.5.1 GIS Mapping of Condition Scores

GIS will be used to visualize:

- Pavement condition distribution
- Bridge crack severity hotspots
- Unified Condition Score (CS) across the network

Heat maps will highlight critical areas requiring immediate attention.

13.6 Maintenance Priority Maps

The Maintenance Prioritization Score (MPS) will be mapped spatially to show:

- High-priority assets
- Medium-priority assets
- Low-priority assets

This allows decision-makers to quickly identify clusters of deteriorated assets.

13.7 Decision-Support Dashboards

Interactive dashboards will be developed to display:

- Condition trends
- Traffic and risk overlays
- Cost estimates
- Maintenance scenarios

These dashboards will support strategic planning and resource allocation.

13.8 Benefits of GIS Integration

GIS enhances the framework by:

- Improving transparency
- Supporting spatial decision-making
- Enabling long-term maintenance planning
- Facilitating communication with stakeholders

14. Limitations of the Study

The proposed framework is designed to be comprehensive and practical, several limitations must be acknowledged to ensure transparency and guide future research.

14.1 Data Availability and Quality

The accuracy of AI models depends heavily on the quality and completeness of the datasets provided by government agencies. Potential limitations include:

- Missing or inconsistent pavement distress records
- Limited availability of high-resolution bridge images
- Variability in inspection practices across years
- Incomplete traffic or climate datasets

These limitations may affect model performance and generalizability.

14.2 Model Generalization

AI models trained on Abu Dhabi's datasets may not generalize perfectly to:

- Other emirates
- Rural areas

- Different climatic zones
- Networks with different construction standards

However, the framework can be adapted with retraining.

14.3 Computational Requirements

Deep learning models, especially CNNs, require:

- High computational power
- GPU acceleration
- Large, annotated datasets

This may limit real-time deployment unless optimized.

14.4 Subjectivity in MCDM Weighting

An expert judgment is essential for assigning weights in the MPS model, it introduces:

- Subjectivity
- Potential bias
- Variability across agencies

Sensitivity analysis will be used to mitigate this limitation.

15. Research Scope

15.1 Spatial Scope

The geographical scope of this study is limited to some of the road and bridge networks within the Emirate of Abu Dhabi, United Arab Emirates. Accordingly, the findings and recommendations are intended to be applicable to this networks and may not be directly generalizable to other regions with different environmental, traffic, or infrastructure characteristics.

15.2 Time Scope

- The study is based on the data available during the data collection period. The datasets utilized include:
- Bridge inspection reports.
- International Roughness Index (IRI) measurements.
- Falling Weight Deflectometer (FWD) test data.
- Traffic volume and road traffic accident records.
- Historical maintenance and rehabilitation records.

15.3 Thematic Scope

The study focuses on the following areas:

- Assessment of pavement condition.
- Assessment of bridge condition.
- Development of Artificial Intelligence (AI) models for predicting pavement and bridge conditions.
- Development of an optimization algorithm for prioritizing maintenance and rehabilitation interventions.

The study does not address:

- Detailed economic or financial analyses.
- Advanced traffic engineering and transportation modelling.

15.4 Data Limitations

The accuracy and reliability of the proposed Artificial Intelligence models depend on the availability of sufficient, accurate, and high-quality data. Missing, incomplete, or inconsistent datasets may reduce the predictive performance of the developed models. Furthermore, Structural Health Monitoring (SHM) data may not be available for all bridges included in the study, which may limit the comprehensiveness of the bridge condition assessment.

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List of Abbreviations

AI Artificial Intelligence



ANN Artificial Neural Network

AADT Annual Average Daily Traffic

CNN Convolutional Neural Network

CS Condition Score

DMT Department of Municipalities and Transport

FWD Falling Weight Deflectometer

GIS Geographic Information System

IRI International Roughness Index

MCF Maintenance Cost Factor

ML Machine Learning

MPS Maintenance Priority Score

PCI Pavement Condition Index

RSL Remaining Service Life

RF Random Forest

RS Risk Score

SHM Structural Health Monitoring

SVM Support Vector Machine

TI Traffic Importance

UAE United Arab Emirates

YOLO You Only Look Once (Object Detection Model)

Prepare by

Ahmed Mubark Mohammed Ali