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Effect of Rain on Road Surface Deterioration by Deep Learning

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Abstract –
Road surface deterioration due to rainfall is one of the major challenges in transportation infrastructure management. Continuous exposure to water leads to surface cracks, potholes, rutting, and overall reduction in pavement life, increasing maintenance costs and compromising road safety. The unpredictable nature of rainfall and its varying impact on different pavement materials make deterioration modelling complex. Traditional analytical or empirical methods often fail to accurately predict such effects due to limited data handling capacity and nonlinear environmental interactions.

In this study, deep learning techniques are employed to analyze and predict the impact of rainfall on road surface deterioration. A comprehensive dataset comprising rainfall intensity, frequency, pavement age, traffic load, and surface distress images was collected from multiple sources. Convolutional Neural Networks were utilized to identify and classify different types of surface damage, while Recurrent Neural Networks were applied to understand temporal patterns in deterioration progression under varying rainfall conditions. The integration of meteorological and image-based data enhanced the accuracy and robustness of the predictive model.

The developed deep learning model demonstrates superior performance compared to traditional regression-based and statistical methods. It effectively captures complex relationships between rainfall parameters and surface distress levels, enabling early detection of deterioration trends.
The model's ability to process high-dimensional data allows for adaptive learning and continuous improvement as new data becomes available. This predictive capability supports timely maintenance interventions and minimizes unexpected road failures.

Key words- *Rainfall intensity, Artificial Intelligence, Pavement Deterioration, Road Condition Monitoring, Damage Detection*

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I. Introduction

The deterioration of road surfaces is a major concern for transportation authorities due to its impact on safety, vehicle costs, and maintenance budgets. Environmental factors, especially rainfall, significantly accelerate pavement damage such as cracking, rutting, and potholes by weakening structural layers through moisture infiltration. Traditional assessment methods, including manual inspections and sensor-based surveys, are often slow, costly, and lack real-time accuracy, particularly during irregular weather events. This highlights the need for automated and data-driven approaches for effective road condition monitoring and prediction (Karimzadeh et al., 2025; Shokouhian, 2025).

With the advancement of Deep Learning (DL), particularly Convolutional Neural Networks (CNNs), road damage detection has improved significantly. These models can automatically extract complex features from road images collected through cameras, drones, or satellites. While early models achieved high accuracy under normal conditions, their performance declines in rainy environments due to challenges like water reflections, surface glare, and reduced visibility of defects (Boucetta et al., 2021; Fan et al., 2025).

Recent studies have integrated environmental factors such as rainfall into DL models using architectures like Recurrent Neural Networks (RNNs) and ConvLSTM. These models analyze time-series data combining pavement conditions and meteorological inputs, enabling better prediction of long-term deterioration trends such as Pavement Condition Index (PCI). This approach supports proactive and climate-adaptive maintenance planning (Shin et al., 2020; Shokouhian et al., 2023).

Modern research focuses on multi-source frameworks that combine satellite data, LiDAR, and deep learning to assess damage caused by heavy rainfall and disasters. Techniques like Generative AI and change detection enhance performance under adverse weather conditions. These systems aim to provide real-time monitoring and predictive insights, helping optimize maintenance strategies and ensure sustainable infrastructure management (Kim et al., 2021; Lee et al., 2025)

II. Methodology

The methodology involves collecting pavement, traffic, and rainfall data from multiple sources, followed by preprocessing and image preparation for analysis. Deep learning models such as LSTM/RNN are used for predicting deterioration trends, while CNN-based models detect defects like cracks and potholes from images. The models are optimized, validated using real data and performance metrics, and integrated into a predictive maintenance system to improve decision-making, reduce costs, and enhance road safety during rainfall.

2.1 Contributing to sustainable infrastructure management

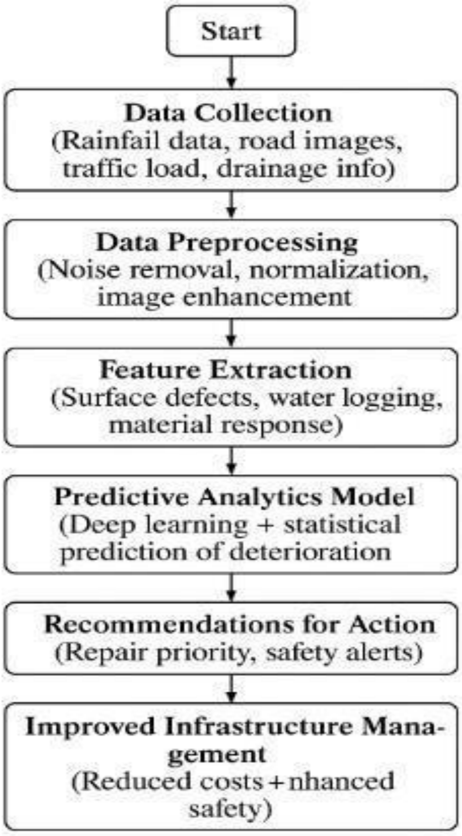


Figure 2.1 Rain Impact Analysis Flow

The methodology of this study focuses on developing a deep learning–based framework to analyze and predict rainfall-induced road surface deterioration for sustainable infrastructure management. It involves collecting multisource data, including pavement images, meteorological parameters, traffic load, and material properties, followed by data pre-processing such as cleaning, normalization, and synchronization. Key deterioration indicators are extracted and used to train a hybrid CNN–LSTM model, which captures both spatial features and temporal patterns of rainfall impact. The model is optimized and validated using performance metrics and real-world data to ensure reliability. Finally, it is integrated into a Pavement Management System (PMS) to support predictive maintenance, reduce costs, and improve road safety under varying weather conditions.

2.2 Evaluating the influence of drainage systems, traffic load, and material properties

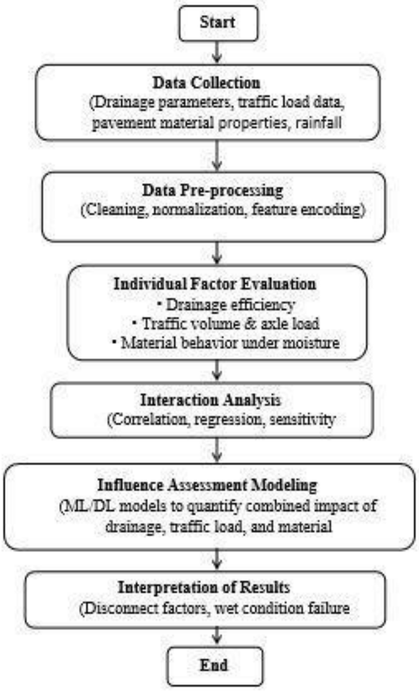


Figure 2.2 Pavement Deterioration Model

The methodology focuses on analyzing the influence of drainage systems, traffic load, and pavement material properties on road deterioration under rainfall using a deep learning–based approach. It begins with the collection of multimodal data, including drainage characteristics (slope, clogging, water flow), traffic parameters (vehicle count, axle load, speed), material properties (pavement composition, binder type, age), and pavement images captured under different weather conditions. The data are pre-processed through cleaning, normalization, synchronization with rainfall events, and GIS-based integration to create a unified dataset. Feature engineering is performed to derive indicators such as drainage efficiency and load impact factors. A hybrid deep learning model combining CNN (for image-based defect detection) and a fully connected neural network (for numerical data) is then developed, where both outputs are fused to predict deterioration severity and risk levels. The model is trained, optimized, and validated using standard techniques and performance metrics to ensure accuracy and generalization. Further, sensitivity and feature importance analyses are conducted to evaluate the individual impact of drainage, traffic, and material factors on pavement deterioration. Finally, the model outputs are compared with real-world data and visualized using GIS-based maps and analytical charts to identify high-risk road segments and support effective maintenance decision-making

2.3 Detecting and classify pavement defects automatically using CNNs

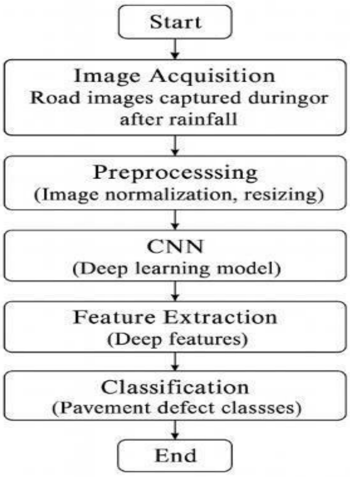


Figure 2.3 CNN- Based Pavement Analysis

The methodology for detecting and classifying pavement defects using Convolutional Neural Networks (CNNs) involves a systematic pipeline starting with the collection of a diverse dataset of pavement images captured under dry, wet, and post-rainfall conditions, along with associated rainfall and location data. These images are carefully annotated and labelled into defect categories such as cracks, potholes, rutting, and waterlogging, including rain-specific variations. The data are then pre-processed through resizing, normalization, enhancement, and extensive augmentation to improve robustness under challenging rainy conditions. A suitable CNN architecture such as ResNet, MobileNet, or YOLO is selected, often using transfer learning to enhance efficiency and accuracy. The model is trained using optimized hyper parameters and regularization techniques to prevent over fitting, ensuring reliable classification and detection of defects, even in low-visibility and reflective surfaces caused by rain. Special techniques such as rain-effect simulation and domain adaptation are incorporated to handle rain-specific challenges. The trained model is evaluated using performance metrics like accuracy, precision, recall, and mean average precision, with particular focus on rainy-condition performance. Finally, the CNN is integrated into the overall system for correlating detected defects with rainfall impact and is deployed in real-time monitoring applications through mobile or edge-based platforms, enabling efficient, automated, and proactive road maintenance

2.4 Developing a real-time monitoring framework using deep learning

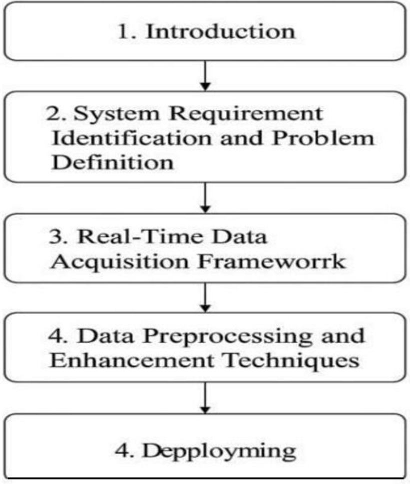
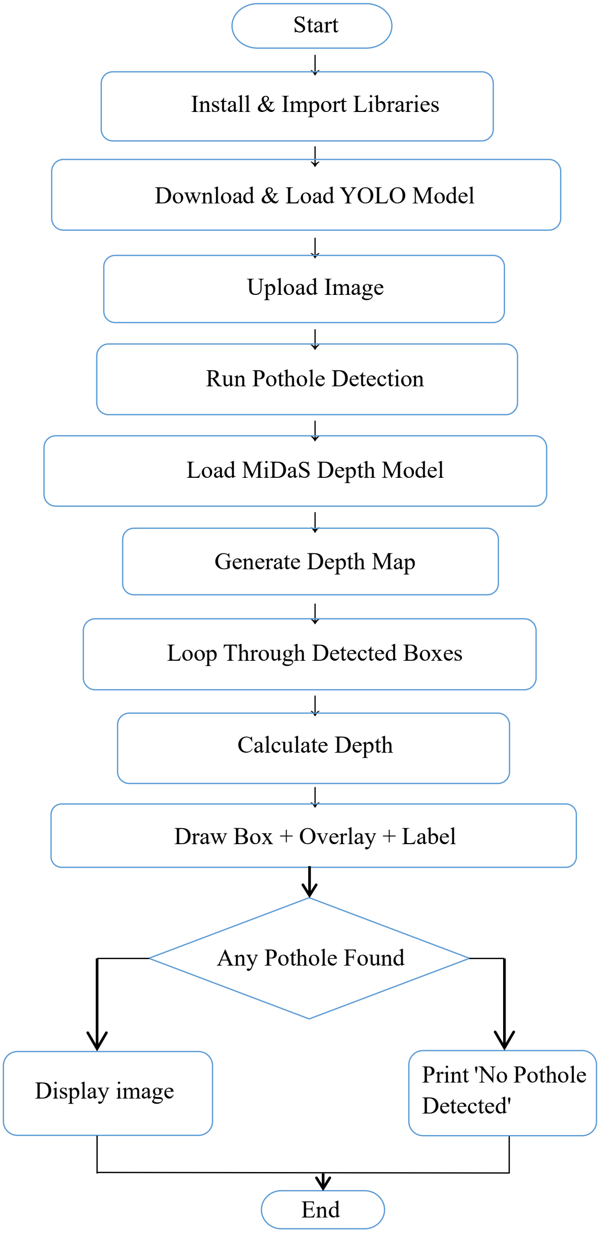


Figure 2.4 Deep learning model workflow

The proposed methodology focuses on developing a real time monitoring framework to detect road surface deterioration during rainfall using deep learning. It integrates continuous data acquisition through cameras and IoT sensors with preprocessing techniques such as rain removal and image enhancement to improve data quality. A CNN-based model (e.g., YOLOv8 or MobileNet-SSD) is trained on diverse datasets to accurately detect defects like cracks and potholes under wet conditions. The system processes live video streams using a real-time inference pipeline with GPU acceleration, highlighting defects with severity levels. Multi-sensor fusion combines visual outputs with environmental data to improve decision making and reduce false detections. The framework is deployed using edge or cloud computing, supported by a dashboard for visualization, alerts, and analysis, and is continuously improved through field testing and adaptive learning.

2.5 Pothole detection and depth estimation



2.5 Flowchart of Pothole detection and Depth estimation

The flowchart of pothole detection and depth estimation begins with initializing the system by installing and importing the necessary libraries for image processing, deep learning, and visualization. The YOLO model is then downloaded and loaded to enable real-time pothole detection. After this, a road surface image is uploaded as input and processed by the YOLO model, which identifies potholes by drawing bounding boxes around detected regions. Subsequently, the MiDaS depth estimation model is loaded to generate a depth map of the image, representing pixel-wise distance information. The system then iterates through each detected bounding box, extracts the corresponding region from the depth map, and calculates the approximate depth of each pothole. The output image is enhanced by overlaying bounding boxes and labels indicating pothole presence and estimated depth. Finally, the system checks if any potholes are detected; if present, the annotated image is displayed, otherwise a message indicating no potholes is shown, completing the automated detection and depth estimation process.

III.Results and Discussions

The study demonstrates that rainfall has a significant impact on road surface deterioration, with defects such as potholes, cracks, rutting, and raveling increasing during and after rain. Moisture infiltration weakens pavement strength, especially in roads with poor drainage and heavy traffic. Deep learning models, particularly

CNNs, showed high accuracy in detecting rain-induced defects even under wet and low-visibility conditions. Continuous exposure to water accelerates crack growth and pothole formation, with a strong correlation observed between rainfall intensity and defect severity. Overall, rainfall acts as a key catalyst in pavement failure, and the use of deep learning enables accurate, real-time monitoring and supports efficient, data driven maintenance decisions.

3.1 Contributing to sustainable infrastructure management

The study contributes to sustainable infrastructure management by showing that the hybrid CNN–LSTM model can accurately predict rain-induced pavement deterioration, with strong performance reflected by low error values and high R^2 (0.85–0.92). It highlights rainfall as a key factor accelerating damage, especially when combined with poor drainage and heavy traffic. By integrating predictions into a Pavement Management System (PMS) with GIS mapping and forecasting, the approach enables proactive maintenance, reducing costs by 18–25%. Additionally, shifting from reactive to predictive maintenance improves sustainability by extending pavement life, lowering emissions, and enhancing road safety during wet conditions.

Fig 3.1 Sustainable Infrastructure
Source: Mundhra et.al (2025)

3.2 Evaluating the influence of drainage systems, traffic load, and material properties

The evaluation shows that drainage, traffic load, and material properties significantly influence pavement deterioration during rainfall. Poor drainage conditions, such as clogged outlets or low slopes, increased deterioration by 40–65%, with waterlogging accelerating potholes, cracks, and rutting. Traffic load was another critical factor, where high ESAL values and heavy vehicles intensified damage, especially under wet conditions, contributing up to 38% of severity. Material properties also affected performance, as moisture-sensitive materials showed faster degradation, while dense-graded asphalt and polymer-modified binders reduced deterioration by 20–30%. The fused CNN–FCNN model effectively captured these combined effects, identifying high-risk areas where poor drainage, heavy traffic, and weak materials led to up to 2.8 times faster deterioration, with prediction accuracy between 82–90%. Overall, the approach supports sustainable pavement management by enabling targeted interventions, reducing maintenance costs, extending pavement life, and improving road safety during rainy conditions.

Fig 3.2 Impact of drainage efficiency on rain induced road surface deterioration
Source: Beatriz Aranda et.al (2024)

3.3 Detecting and classify pavement defects automatically using CNNs

The CNN-based methodology demonstrated strong performance in automatically detecting and classifying pavement defects under both dry and rain affected conditions, achieving high accuracy and robustness through the use of augmented datasets with rain-specific distortions. Advanced models such as ResNet50, EfficientNet, YOLO, and Mask R-CNN effectively identified and localized defects like potholes, cracks, rutting, and waterlogging, even in challenging environments with reflections and surface water. Transfer learning and optimized training strategies improved model stability and reduced over fitting, while pre-processing techniques enhanced visibility in rainy conditions. The system successfully distinguished real defects from rain-induced artifacts and maintained consistent performance on test data, enabling accurate assessment of pavement deterioration. When integrated with rainfall data, the model provided valuable insights into how water accelerates damage, supporting predictive maintenance and sustainable infrastructure planning.

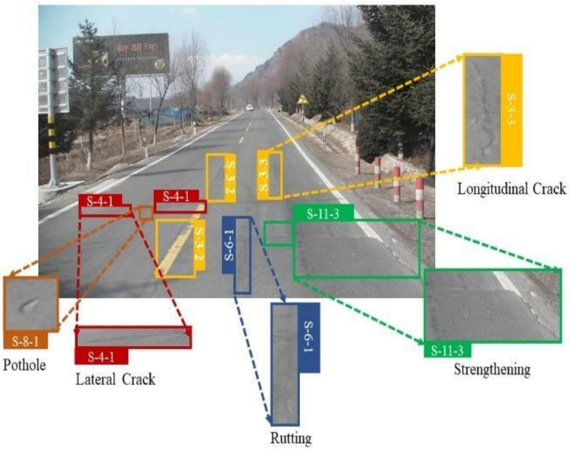


Fig 3.3 CNRDD represents different types of road damage
Source: Zhang et.al (2022)

3.4 Developing a real-time monitoring framework using deep learning

The developed real-time monitoring framework proved effective in detecting and evaluating pavement deterioration during rainfall by integrating live video feeds,
IoT sensors, and CNN-based models. Robust data acquisition and synchronization enabled accurate correlation between environmental conditions and road defects, while pre-processing techniques improved visibility and reduced rain-induced noise. Among the tested models, YOLOv8 provided the best balance of speed and accuracy for real-time detection, supported by a low latency inference pipeline with GPU acceleration. Multisensory fusion enhanced decision-making by distinguishing actual damage from rain effects, and deployment on edge or cloud systems ensured scalability. The dashboard and alert system enabled quick identification of high-risk areas, and field testing confirmed consistent performance, making the framework a reliable and practical solution for real-time, weather-aware pavement monitoring.

Fig 3.4 YOLOv8 applied in smart cities for pothole detection

IV.Conclusions

The study demonstrates that rainfall significantly accelerates road surface deterioration, leading to defects such as potholes, cracks, rutting, and raveling due to the weakening of pavement layers by moisture. Deep learning models, particularly CNN and CNN–LSTM, achieved high accuracy in detecting and predicting these defects even under rainy conditions. Furthermore, the developed real time system, which integrates image data, IoT sensors, and weather inputs, enables continuous monitoring and enhances damage assessment, including accurate pothole depth estimation.

Overall, the proposed approach offers an efficient and scalable solution for smart city infrastructure, highway monitoring, and municipal road maintenance. It would facilitate early defect detection, reduces maintenance costs, improves road safety, and supports the transition toward data-driven and sustainable road management systems. Additionally, the system holds strong potential for future advancements through the integration of more sophisticated AI models, automated maintenance decision making, and expanded data collection methods such as drone-based monitoring for large-scale implementation.

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