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An Overview of Machine Learning Techniques for Evaluation of Pavement Condition

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***Abstract*—Pavement management systems play a vital role in the development of a country as it is a very important part of the economy. Maintaining a good quality of the road is the key duty of the road authorities. They require methods for pavement-related data collection and analysis to evaluate its condition. Machine learning (ML) methods can be utilized for defect classification from an image, defect recognition and segmentation in the assessment of pavement distress. This paper presents an overview of the machine learning techniques used to analyze pavement condition data. Moreover, information collection methods and pavement condition indices are also studied from the point of view of ML algorithms. Future research directions are also presented by highlighting the limitations of using ML techniques for the assessment of pavement conditions.**

Keywords—Pavement Condition, Machine Learning, Pavement Management, Image Processing, Artificial Neural Network (ANN), Convolutional Neural Network (CNN)

I. Introduction

Pavement is one of the most significant civic setups for the movement of automobiles and people in contemporary transportation. For civil engineers, pavement service superiority and useful life are critical since they directly impact the users' regular service. Monitoring the condition of pavements and performing appropriate repairs are therefore critical for public transportation safety [1].

The Pavement Quality Index (PCI) is a measure that assesses a pavement's or road's overall surface quality. It is measured on a numerical scale of 0 to 100. The United States Army Corps of Engineers established this statistical metric, which needs manual/visual examination and inspection of the needed routes. PCI surveying techniques for roads and airport pavements were standardised by ASTM International (a worldwide standards organisation that creates and publishes voluntary consensus standards for a variety of services, goods, and systems). As a result of the quantitative assessment awarded to roads, it employs verbal criteria ranging from "failed" to "excellent." The goal of highway preservation and restoration is to enhance the state of a pavement system to decrease expenses, boost useful service life, reduce carbon footprint, and increase the safety of road users [2].

The main pattern for measuring the physical and useful status of civic infrastructures is a manual visual examination. Defective inspections and condition assessments, however, continue to cause accidents. Pavement faults also cost Indian drivers crores of rupees in repairs each year, according to the Ministry of State for Road Transport & Highways Government of India. To summarise, road surface inspection to discover faults is critical for ensuring traffic safety [3].

Different features of the application of machine learning techniques to pavement predictive analysis can be differentiated: pavement quality is indicated by International Roughness Index (IRI), the emphasis of neural networks in determining the IRI, creation of databases which last long-term [4].

This study does not concentrate just on the construction of the most extensively used approaches but instead provides a quick overview of the many procedures that have been created, including ANNs for prediction and CNNs for image processing and recognition. The various indications or magnitudes to be identified are then discussed.

II. PCI Index

The PCI gives a measure of the current state of a pavement or roadway based on the quantity and types of 'distresses' noticed on its exterior, which by implication suggests mechanical integrity and external operating condition, but it does not assess the mechanical capacity of the pavement. It does, however, give a reasonable and objective foundation for identifying the need for maintenance and repair.

Alligator cracking, bumps, depressions, and potholes are among the 'distresses' listed before. They're given a severity level (low, medium, or high) based on how they influence 'riding quality,' a self-explanatory phrase that's likewise defined with the benchmarks low, medium, or high depending on how the distresses affect a vehicle moving at normal running speed. This study produces a number between 0 and 100, with 100 denoting the best possible situation and 0 denoting the worst likely condition as shown in Fig. 1.

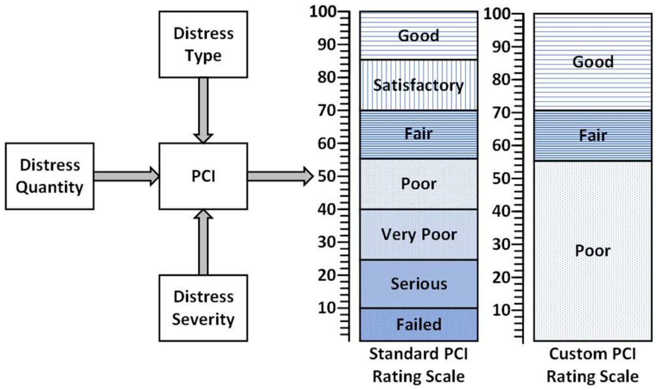

Fig. 1. Range Scale of PCI

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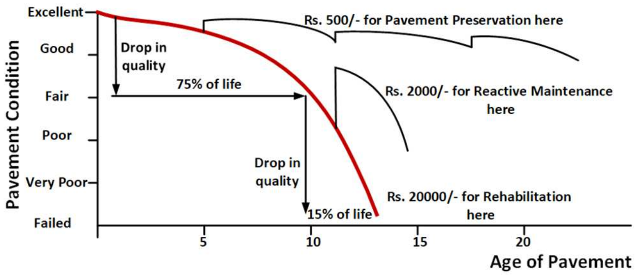

Fig. 2. Pavement Maintenance Chart

Certain countries utilised different indices to measure ride quality/roughness or surface distress/rating before the PCI was developed as the go-to index for gauging road and pavement conditions, but they were not standardised methodologies and did not account for essential aspects. Some countries still use these old outdated systems; however, the majority now use the PCI, not only because it is typically a collection of the above metrics, but also because it accounts for considerations like structural capacity and friction and allows for the tracking of distresses over time, which are not acknowledged by pre-existing indices. The Pavement Condition Index was developed, successful, and widely disseminated as a result of a demand for a more complete assessment of pavement performance, bolstered by an international emphasis on ride quality [5].

One can essentially determine the pace of road deterioration by monitoring the PCI regularly, which allows one to identify repair and rehabilitation needs far ahead of time, which undoubtedly saves money in the long run as shown in Fig. 2. The PCI not only provides performance input for validation but also allows to enhance (and ultimately revolutionise) road and pavement design and maintenance operations. The local government, on the other hand, turns a blind eye to the deteriorating infrastructure when the PCI might easily become the standard approach for assessing and improving road conditions. Nonetheless, interested NGOs may help revolutionise road quality assessment at the very least by simplifying the PCI for citizens and enabling their involvement in supplying reliable data to the government - something that would undoubtedly attract their attention. Moreover, these techniques can be aided and improved significantly by the use of machine learning algorithms [6], [7].

III. Pavement Condition Indicators

The mechanical characterization of the roadway, taking into account its physical structure, is part of the pavement condition evaluation (e.g., coarseness, friction, distress type, etc.). For this purpose numerous indices were created, with the PCI, Pavement Serviceability Index (PSI), IRI and Pavement Quality Index (PQI) being the most often used [8].

A. PCI, PSI, IRI and PQI

Surface distress is the most important influencing element for PCI calculation, and it is determined by the following factors: distress type, severity level, and concentration of distress. As a result, it is a good index to use when extrapolating imaging difficulties to PCI calculations.

The PSI calculates the serviceability grade based on measurements of many physical criteria such as rut, cracking, roughness and penetration from surface distresses. It has a scale of 0 to 5, with 0 being the worst and 5 being the finest.

Computed linear road profiles, i.e. vertical nonconformities or abnormalities of the roadway surface from a planar plane, are the most prevalent source of the IRI. It's generated using a quarter-car automobile mathematical system, whose responses are added together to provide a roughness index using slope units. After making profilometric measurements on road pavements with specialized laser instruments, the IRI index may be calculated. The PQI calculates the complete roadway condition by combining the magnitudes of roadway coarseness and distress [9].

B. ML metrics

Different measures that link the actual data to the anticipated data are used to determine how optimum the produced model is [10], [11]. The most often utilised metrics in ML algorithms for classification and regression issues as pavement evaluation methodologies are shown in Table I.

TABLE I. ML Metrics

Metric	Formula
Accuracy	$\frac{TP + TN}{\text{Total Images}}$
True Positive (TP) Rate	$\frac{TP}{TP + FN}$
True Negative (TN) Rate	$\frac{TN}{TN + FP}$
Precision	$\frac{TP}{TP + FP}$
F1-score	$\frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}}$
Recall	$\frac{TP}{TP + TN}$

Fracture, non-crack, ravelling, non-rutting, and other patterns that are accurately categorized with defect categories detection are instances of classification issues in pavement evaluation Depending on the investigation, other pavement markers might be classified as highway friction estimations or existing road characteristics. Crack assessment is a challenging duty to do to keep the public safe since cracking can speed up the deterioration process. Accuracy is defined as the proportion of correct predictions to the total number of incidents. The percentage of correctly recognized positive patterns is measured by sensitivity. The percentage of correctly classified negative patterns is referred to as specificity. The f1-score is the modulation index of Precision and Recall, and it represents the percentage of correct positive overall observations which should have been classified as affirmative. The number of valid favourable aspects divided by the total of favourable results expected determines precision [12], [13].

Regression measures such as Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RSME), and R-Squared are used to evaluate issues to predict continuous variables such as IRI or PCI. MSE is a metric that calculates the average of the squares of the errors, RMSE $=$

$\sqrt{MSE}$, MAE is the average of the absolute variance between the errors and R^2, where, R = correlation coefficient = strength of association between projected and observed scales [14].

IV. ML Approach – A Review

A. *ML Algorithms*

Table II gives a quick summary of generally used techniques, as well as an in-depth examination of the widely used machine learning methods for the construction of road maintenance services [15].

TABLE II. ML Algorithms

Metric	Summary
Support Vector Machine (SVM) [6], [16]	It usually delivers great accuracy; it prohibits theoretical promises against overfitting; accurateness and performance are size-independent; it handles extremely large data accurately and has good generalisation capacity; Outliers have a lower influence. Accurateness is dependent on the no. of training cycles; huge datasets take longer to process; overlapping classes perform poorly, and suitable hyperparameters and kernel functions are required.
Decision Tree [17], [18]	It's simple to understand and describe how features interact; they can handle numbers, names, and text; no normalization is required, and unrelated characteristics have no effect. It struggles with extremely large; overfitting issues when proper pruning is lacking; and sensitivity to data changes.
k-Nearest Neighbour (k-NN) [19]	Easy to comprehend and execute; no data norms (e.g., variable dependence); suitable for multi-modal classes; model adapts effectively to additional information points. Lower efficiency for high-dimensional data; performance is based on choosing a reasonable "k" value; performance varies depending on data size; it does not operate well on unbalanced information.
k-means [20]	It is very straightforward to build; it scales to huge information sets; it frequently assures union; it is easy to adapt to new cases; it generalizes to a variety of cluster shapes and sizes (e.g., elliptical). It is reliant on the "k" value; it has issues with clusters of varied sizes and density; outliers can pull centroids, and it suffers from a large number of dimensions.
Naïve Bayes [21], [22]	Converges quickly; reduces calculation training time; ascendable with huge information sets; unresponsive to unrelated characteristics; sufficient performance with extremely large data. Inaccurate data representation; faulty estimator; assumes that all predictors are independent; gives 0 probability to a categorical variable whose category in the test data set was not available in the training dataset which seldom happens in actual cases (zero-frequency problem).
Random Forest [23]	They are fast, scalable, and resilient to noisy data; they do not overfit; they are simple to comprehend; they have a lower prediction error, and they work well on unbalanced datasets. It copes effectively with large volumes of data and missing data, and outliers have minimal influence. It's difficult to understand the various parameters; they're found to be prejudiced with data attributes; not suitable for similar technology with sparsity attributes; slow for actual forecasting as the trees (estimators) grow.
Artificial Neural Network (ANN) [9]	Depending on aspects like the number of weights in the network, the number of training instances evaluated, and the settings of various learning algorithm parameters, as the training examples may contain errors that do not affect the final output, they are extremely resilient to noise in the training data. They require parallel processing processors (hardware), which makes it more difficult for ANN to understand the issue statement; the ANN solution to the problem statements is based on an assumption that we do not understand.
Convolutional neural networks (CNN) [24]	In classification, localization, semantic segmentation, and action identification tasks, CNN-based models produce state-of-the-art performance; they use less computing than typical ANN (convolutional operation) and are very good at picture classification and recognition since they use the same information in all image places. They detect comparable photos with varying noise levels as the same picture; they classify images with varied placements; they classify images with different noise levels as the same picture. As CNN's lack coordinate frames, which are an important part of human vision, GPUs are frequently required.

B. *For Image Processing*

Image-processing techniques for determining road conditions are thought to be promising non-destructive testing tools for quantifying pavement distresses by examining pavement surface photographs. Many frameworks are now including computer vision (CV) modules as a standard feature. In this regard, the current section discusses cutting-edge CV approaches for automating the defect and damage identification procedure. As a result, a real-time forecast of drivable surface conditions would undoubtedly help active safety systems and self-driving vehicles.

The steps involved in image processing for crack identification are shown in the form of a block diagram in Fig. 3. These six steps are used in many algorithms, however, classification algorithms may consist of an ML or hybrid ML algorithm to improve classification accuracy [25].

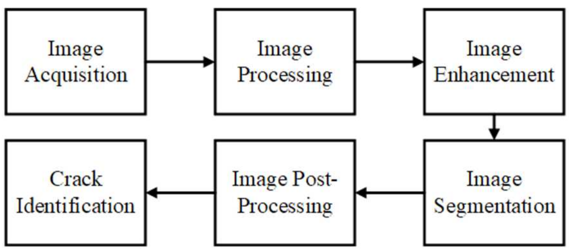

Fig. 3. Steps involved in image processing for crack identification

Effective pavement repair programmes can only be designed with accurate forecasts of future pavement cracking rates based on quantitative analyses of prior and current pavement conditions. To give essential quantitative estimates of fractures in pavement surface pictures, image-based crack-recognition algorithms were used. A collection of low-intensity pixels relative to nearby pixels can be characterized as a crack in CV. To deal with multi-level topological geometries of crack pictures, several image processing stages must be applied for computer-aided crack recognition [26].

Previously, identifying and quantifying the severity, kind, and extent of surface cracking was a difficult aspect of assessing asphalt pavements. Due to their affordability in terms of information collecting and processing, image-based fracture detection systems have been widely researched. The most pertinent issue is that automated pavement distress detection and categorization has remained one of transportation authorities' top research priorities. To minimize preventative road repair, image categorization based on machine learning models is becoming the primary application and research tool. Image-based models, on the other hand, are primarily concerned with fracture detection and categorization.

Furthermore, in recent years, the state-of-the-art has centred on various image preprocessing approaches and architectures, with CNN's being the most extensively employed, as well as transfer learning resources as shown in Fig. 4 [24], [27].

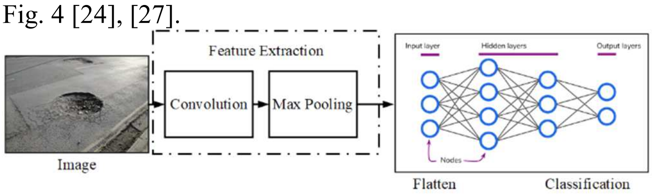

Fig. 4. Representation of CNN-based image classification

V. Conclusion

One of the most essential civic infrastructures is pavement. It is vital to examine the condition of the pavement and perform regular maintenance to guarantee its functioning and safety. Currently, civil engineers gather pavement dynamic response data using a range of invasive sensing technologies and assess surface conditions using image processing techniques and machine learning algorithms based on pavement pictures. Pavement surface distress and structural state may be successfully discovered, categorized, and evaluated using machine learning approaches. Most studies employed SVM and ANN as classifiers for pavement flaws in the early stages since the accuracy met the technical criteria at the time. Deep learning algorithms like CNN have improved outcomes for pavement distress diagnosis and performance evaluation as computer technology has developed because of its local connectivity and weight sharing. The diverse functions of machine learning approaches may help civil engineers solve various pavement monitoring difficulties, such as recognizing the types of pavement fractures and marking the area of pavement damage. However, future research should take into account the following points:

(1) To generate a significantly bigger dataset, more field/laboratory testing on pavement performance and conditions is required.

(2) The flexibility of machine learning algorithms for pavement photographs recorded by modern equipment and done under adopting different conditions should be increased.

(3) Much of the research at this point is also focused on identifying pavement fractures. Hence, machine learning approaches, those of which are previously classified may further be used for training based on a range of various pavement distresses in the future to forecast the pavement performance reliably.

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