

Article

Distress-Level Prediction of Pavement Deterioration with Causal Analysis and Uncertainty Quantification

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Abstract

Pavement performance prediction serves as a core basis for maintenance decision-making. Although numerous studies have been conducted, most focus on road segments and aggregate indicators such as IRI and PCI, with limited attention to the daily deterioration of individual distresses. Subject to the combined influence of multiple factors, pavement distress deterioration exhibits pronounced nonlinear and time-lag characteristics, making distress-level predictions prone to disturbances and highly uncertain. To address this challenge, this study investigates the distress-level deterioration of three representative distresses—transverse cracks, alligator cracks, and potholes—with causal analysis and uncertainty quantification. Based on two years of high-frequency road inspection data, a continuous tracking dataset comprising 164 distress sites and 9038 records was established using a three-step matching algorithm. Convergent cross mapping was applied to quantify the causal strength and lag days of environmental factors, which were subsequently embedded into an encoder–decoder framework to construct a BayesLSTM model. Monte Carlo Dropout was employed to approximate Bayesian inference, enabling probabilistic characterization of predictive uncertainty and the construction of prediction intervals. Results indicate that integrating causal and time-lag characteristics improves the model's capacity to identify key drivers and anticipate deterioration inflection points. The proposed BayesLSTM achieved high predictive accuracy across all three distress types, with a prediction interval coverage of 100%, thereby enhancing the reliability of prediction by providing both deterministic results and interval estimates. These findings facilitate the identification of high-risk distresses and their underlying mechanisms, offering support for rational allocation of maintenance resources.

Keywords: pavement deterioration; distress-level prediction; causal analysis; uncertainty quantification; maintenance decision



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1. Introduction

Pavement performance prediction has long been recognized as a fundamental task in road maintenance and management. Traditionally, research in this field has primarily targeted long-term and periodic maintenance planning, with a focus on macroscopic performance indicators such as the International Roughness Index (IRI) [1,2], Pavement Condition Index (PCI) [3–5], or rutting depth [6,7], typically modeled on an annual or multi-year timescale. While such approaches are suitable for strategic asset management, they fall

short in supporting the increasingly critical demand for routine maintenance in urban road networks. In this context, road agencies are often required to make rapid interventions at the level of individual distress—such as cracks or potholes—where fine spatiotemporal evolution rather than aggregated network-level indices determines the urgency and effectiveness of treatment. Consequently, short-term forecasting of the spatiotemporal evolution of individual distress emerges as a key challenge for enabling precise and timely routine maintenance and forms the central motivation of this study.

A wide range of methods has been developed for pavement performance prediction. Early studies mainly relied on statistical and empirical models [8–10], which established regression-based relationships between pavement condition indices and explanatory factors such as traffic load [11,12], climate [13–15], and material properties [16,17]. With the growing availability of sensing data, machine learning techniques (e.g., support vector regression [18–20], random forests [21,22]) and deep learning architectures (e.g., Long Short-Term Memory (LSTM) [23] and Gated Recurrent Unit (GRU) networks [24,25]) have been increasingly adopted to capture complex nonlinear patterns in deterioration processes. These methods have proven effective in modeling macroscopic performance indicators, where long-term deterioration trends can often be approximated by correlation-based learning. However, when the prediction task is refined to the evolution of individual distresses, the assumptions underlying correlation-based methods become less reliable. Distresses such as cracks or potholes are strongly influenced by external factors—including rainfall [26,27], temperature fluctuations, and traffic loading—that seldom produce immediate effects. Instead, their effects accumulate and appear after a period of delay [28], resulting in time-lag and nonlinear causal effects. At the network or section level, such lagged responses may be smoothed out in aggregated indices [29], allowing correlation-based methods to remain effective. But at the distress level, where localized mechanisms dominate, ignoring these delayed influences risks oversimplifying the true progression process. This underscores the necessity of incorporating causal and time-lag dependencies into predictive modeling, in order to capture the dynamics of distress deterioration more accurately.

Beyond methodological choices, another important consideration is the form of prediction outputs. Much of existing work has focused on deterministic forecasting, where models generate single-valued estimation of future pavement condition [30]. Such outputs are valuable for capturing average deterioration trends, but they may become less reliable in scenarios involving abrupt changes or high variability, which frequently occur at the distress level. The sudden propagation of a crack or the rapid formation of a pothole, for example, is often difficult to capture through point forecasts alone [31]. In recent years, some studies have begun to explore probabilistic or uncertainty-aware forecasting frameworks [32], highlighting the importance of moving beyond single-point estimation. Nevertheless, these approaches remain relatively limited, and their application to distress-level, short-term prediction for routine maintenance is still underexplored. For practical decision-making, where managers must assess both the expected trajectory and the associated risks, the ability to generate forecasts with quantified uncertainty—combining point estimation with confidence intervals—becomes essential. Such outputs would improve interpretability and reliability, enabling predictions to be integrated more effectively into risk-aware maintenance planning.

In addition to methodological considerations, the data foundation for distress-level analysis deserves attention. Much of the existing knowledge on pavement distress deterioration has been conducted from a laboratory perspective or through accelerated loading experiments under controlled conditions. While these studies provide valuable insights into material behavior and mechanistic understanding, they are inherently limited in their ability to replicate the complex interactions of natural environmental factors and in-service

traffic loads. As summarized by Dong et al. [33], much of the deterioration knowledge has been derived from controlled experiments rather than in-service observations. For example, Lv et al. [34] and Cheng et al. [35] investigated the strength and fatigue performance of base materials and asphalt mixtures through laboratory loading and fatigue tests. These studies provide valuable mechanistic insights but are inherently constrained in replicating the complex and variable conditions of field traffic loading and environmental influences. Similarly, research on pavement surface materials has often relied on accelerated weathering tests to evaluate durability, as in the work of Xie et al. [36,37] on reflective cool pavement coatings. Although such tests are effective for comparative evaluation, they cannot fully reproduce the long-term combined impacts of natural climate and real-world traffic. As a result, the deterioration patterns observed under controlled experiments may diverge from those occurring in real-world road networks. This underscores the need for a field-oriented deterioration tracking framework, in which the evolution of individual distresses can be continuously monitored under natural climatic and traffic conditions. Such an approach would enable a more realistic representation of distress progression and provide a stronger empirical basis for short-term predictive modeling in routine maintenance contexts.

Building on these considerations, this study aims to quantify the effects of multiple factors through causal analysis and to enhance model reliability through uncertainty quantification, in order to achieve short-term prediction at the distress level and providing reliable data for maintenance decisions. On the data side, we construct a deterioration chain for individual distresses, in which deterioration events are temporalized to capture their sequential evolution over time under natural environmental and traffic conditions. On the modeling side, we first employ Convergent Cross Mapping (CCM) to examine the causal and time-lag influences of environmental factors on distress progression. Guided by these causal insights, we then develop a Bayesian Long Short-Term Memory (BayesLSTM) network with Monte Carlo dropout, which not only enables short-term distress forecasting but also quantifies predictive uncertainty. In conclusion, these components establish a comprehensive predictive framework designed to characterize distress deterioration more accurately, which can provide maintenance managers with interpretable and risk-aware predictions applicable to routine maintenance plans.

2. Data Preparation

2.1. Data Acquisition

To obtain high-frequency, wide-area pavement distress data, this study deployed a vehicle equipped with the lightweight inspection equipment, as shown in Figure 1a. The real-time acquisition interface is shown in Figure 1b. All devices were synchronized by an in-vehicle industrial PC. A tri-axial accelerometer recorded vehicle vibration at 200 Hz. Positioning data were collected by a high-precision GNSS unit at 1 Hz with accuracy better than 3 m. A front-view and a rear-view camera captured the pavement at a fixed frame rate of 1 Hz, with a resolution of 1920×1080 pixels. The front-view camera faced the traffic direction and covered more than three lanes, serving as the primary source for subsequent distress recognition and analysis. The rear-view camera looked downward behind the vehicle, providing sharper pavement imagery but only for a single lane. During vehicle operation, the camera ensures a spatial resolution at the centimeter scale and can reach millimeter-level precision under optimal conditions.

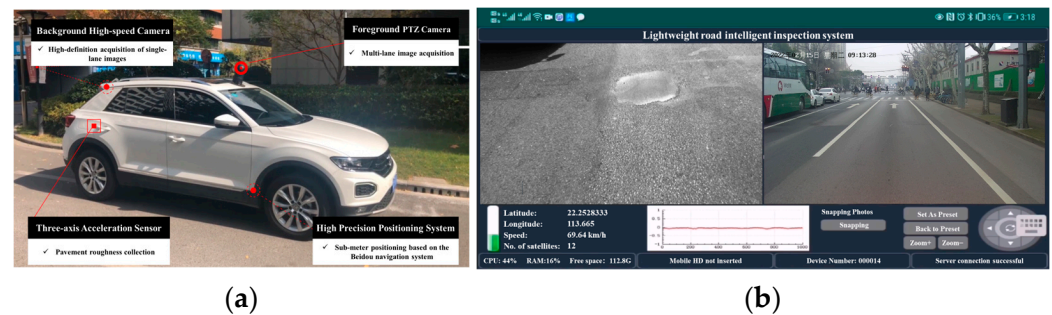


Figure 1. Pavement condition collection. (a) Pavement inspection equipment; (b) Real-time acquisition interface.

The study area is Xuhui District, Shanghai, located in the southwestern of downtown Shanghai. Xuhui has over 270 km of roadways, a land area of 54.93 km², and a resident population of 1.1131 million. It hosts essential transportation hubs such as Shanghai South Railway Station and the Shanghai Tourism Distribution Center, handling crucial traffic flows entering and exiting the city center and connecting neighboring provinces. The resultant heavy and complex traffic imposes considerable stress on pavements and accelerates deterioration, making Xuhui a representative setting for studying pavement performance deterioration. Based on daily inspections, this study compiled a fine-grained pavement distress dataset covering two consecutive years, from 1 January 2022 to 31 December 2023.

It is given that road routine maintenance primarily targets cracks and potholes, whereas rutting, shoving, and ravelling are typically handled via dedicated, periodic programs. This study only focuses on cracks and potholes. Pavement cracks are categorized into transverse, longitudinal, and alligator forms. Longitudinal cracks, which run along the traffic direction, are often linked to construction-related factors (e.g., historic widening, non-uniform base settlement, or improper joint treatment). They usually arise during early operation stages and are weakly related to the natural deterioration process considered here. Therefore, longitudinal cracks are excluded. The analysis hence targets three distress types: transverse crack, alligator crack, and pothole.

2.2. High-Frequency Tracking Dataset

To capture the continuous deterioration process of pavement distresses, it is essential to establish spatiotemporal correspondences across multiple inspection cycles. This enables the construction of dynamic trajectories for the same distress at identical locations, thereby forming continuous tracking sequences that describe how real-world pavement distresses evolve from initial occurrence to subsequent deterioration. Such sequences support distress-level backtracking and facilitate fine-grained monitoring of deterioration. Building on previous work [31], this study proposes a three-level progressive matching algorithm, namely GPS clustering, background matching, and adjacent local area matching, as shown in Figure 2. The first step is employed to group multiple images captured around the same location in order to narrow the matching scope. The second step accounts for differences in shooting perspectives by matching the large-scale road background areas outside the distress region. The third step performs the final precise matching based on the local contour features and relative spatial relationships surrounding the distress area. This hierarchical strategy ensures accurate identification of the same distress instances across different inspection periods, yielding a high-frequency tracking dataset for distress deterioration analysis.

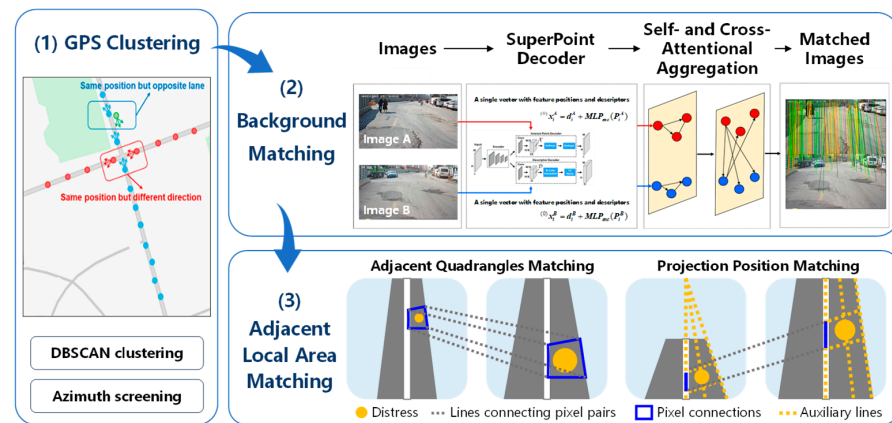


Figure 2. Three-step matching algorithm.

2.2.1. GPS Clustering

As the first step, the spatial search range for distress matching is reduced by clustering pavement images within a certain area using the DBSCAN algorithm. The key parameters of DBSCAN are the clustering radius and the minimum number of samples. Considering that the inspection vehicle acquires GPS data at a frequency of 1 Hz and the average travel speed on urban roads is approximately 40 km/h, the vehicle travels about 11 m/s [31]. Accordingly, the clustering radius was set to 12 m and the minimum number of samples to 1. To further distinguish data collected from opposite driving directions at the same location, azimuth information was introduced. The K-means clustering method was applied to separate images captured during upstream and downstream inspections.

2.2.2. Background Matching

After GPS clustering, the candidate range of potential distress matches is substantially reduced, yielding pavement images nearby. However, since inspection vehicles do not capture images from identical positions during each pass, and camera viewpoints may vary, the same distress can appear at different positions within different images. This introduces challenges for precise one-to-one distress correspondence. To address this issue, this study applies the SuperGlue algorithm [38] to perform background matching across multiple inspection images, establishing correspondences between scene feature points. Specifically, SuperPoint is first employed to detect key points and extract descriptors from the images. These features are then fed into SuperGlue, which leverages a graph-based attention mechanism to learn feature similarity and generate reliable key point correspondences. Based on the resulting matches, the similarity between two images is evaluated, thereby enabling scene-level background matching.

2.2.3. Adjacent Local Area Matching

For most images with clear features and similar backgrounds, the previous two steps are sufficient for reliable matching. However, in cases where the camera viewing angles differ significantly, surface features are weak, or weather conditions introduce interference, pavement distresses may not exhibit obvious correspondences between two images. To overcome this limitation, this study proposes an adjacent local area matching algorithm, which leverages both the similarity of surrounding environments and the relative spatial relationship between the distress and its neighboring context.

Based on the background matching results, pixel-level correspondences between two images can be established. By examining whether matched pixel pairs exist around the bounding box of a distress, two strategies are introduced: matching using adjacent quadrangles and matching using projection relationships. To mitigate the adverse effects of

erroneous key point correspondences, only pixel pairs with confidence scores greater than 0.5 are retained for local feature matching.

(1) Matching using adjacent quadrangles

As illustrated in Figure 3, a pothole is detected in Image A, and its bounding box is $(ax_1, ay_1), (ax_2, ay_2), (ax_3, ay_3), (ax_4, ay_4)$. The center point of this bounding box is denoted as D_a . Let M_A and M_B represent the sets of matched pixel points in Images A and B, respectively. In Image A, the four pixels in M_A closest to the pothole bounding box are selected as the local region, denoted as $(nax_1, nay_1), (nax_2, nay_2), (nax_3, nay_3), (nax_4, nay_4) \in M_A$, forming the quadrilateral region R_a . The corresponding matched pixels in Image B are $(nbx_1, nby_1), (nbx_2, nby_2), (nbx_3, nby_3), (nbx_4, nby_4) \in M_B$, which form the quadrilateral R_b . If the center point of the pothole bounding box in Image B, denoted as D_b , falls within the quadrilateral R_b , the pothole in Images A and B is considered to be the same distress instance.

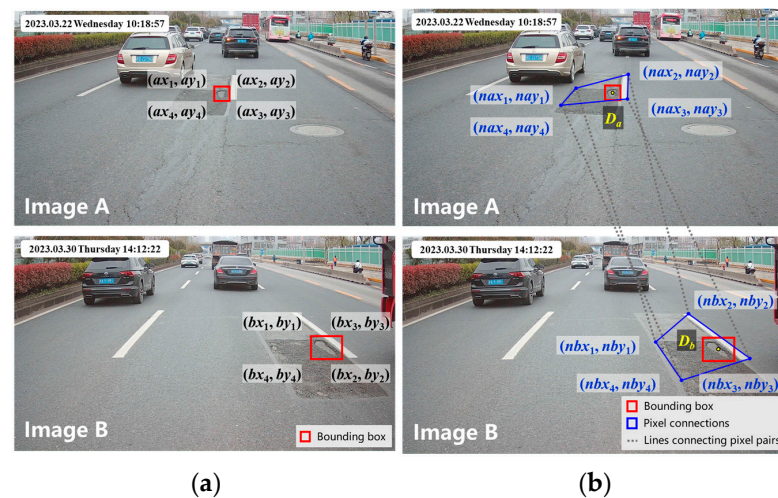


Figure 3. Matching using adjacent quadrangles: (a) Results of background matching; (b) Matching using adjacent quadrangles.

(2) Matching using projection relationships

However, in certain cases, no matched pixels are detected around the distress bounding box, making it impossible to construct a matching quadrilateral for locating the distress, as illustrated in Figure 4.

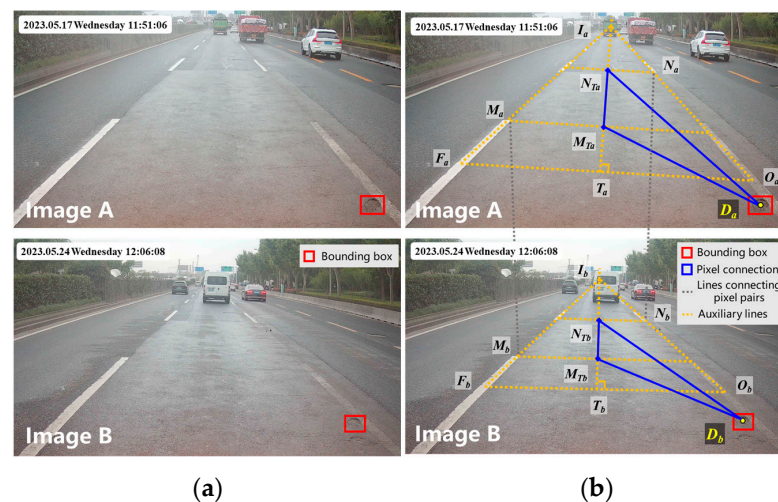


Figure 4. Matching using projection relationships: (a) Results of background matching; (b) Matching using projection relationships.

If no matched pixels are detected around the distress bounding box, the correspondence is determined by the projection relationship between the two images:

- (a) In Image A, the intersection of the two extended lane markings is denoted as I_a .
- (b) A point O_a is selected on the shorter lane marking, and an auxiliary line is drawn through O_a , intersecting the other lane marking at F_a , with $I_a O_a = I_a F_a$.
- (c) A perpendicular line $I_a T_a$ is drawn from I_a to $O_a F_a$, representing the estimated lane centerline direction.
- (d) The same procedure is applied to Image B.
- (e) Two matched pixels M_a and N_a above the distress bounding box are selected.
- (f) Through M_a and N_a , two auxiliary lines parallel to $O_a F_a$ are drawn, intersecting $I_a T_a$ at M_{Ta} and N_{Ta} , respectively.
- (g) Since the projections of objects captured by the vehicle camera on the lane centerline should correspond between the two images, the ratio $h(M_{Ta} N_{Ta}) / h(M_{Tb} N_{Tb})$ represents the projection proportion of the two images.
- (h) Let D_a and D_b denote the center points of the distress bounding boxes in Images A and B, respectively. If the two images capture the same distress, then $D_a N_{Ta}$ and $D_b N_{Tb}$ should satisfy the projection proportion relationship $h(D_a N_{Ta}) / h(D_b N_{Tb}) = h(M_{Ta} N_{Ta}) / h(M_{Tb} N_{Tb})$.
- (i) Considering image distortion and measurement errors, if the projection ratio falls within the range of 0.8–1.2, as defined in Formula (1), the distresses in the two images are regarded as identical.

$$\frac{h(M_{Ta} N_{Ta})}{h(M_{Tb} N_{Tb})} \in [0.8 \times \frac{h(D_a N_{Ta})}{h(D_b N_{Tb})}, 1.2 \times \frac{h(D_a N_{Ta})}{h(D_b N_{Tb})}] \quad (1)$$

2.2.4. Calculation of Pavement Distress Dimensions

To evaluate the deterioration of pavement distresses, it is necessary to calculate the distress dimensions for each inspection. According to the Highway Performance Assessment Standard (JTG H20-2018) [39], alligator cracks and potholes are assessed by area, whereas transverse cracks are assessed by length. Accordingly, this study adopts crack length as the dimension indicator for transverse cracks, and distress area as the indicator for alligator cracks and potholes.

During road inspections, the vehicle-mounted cameras are not perfectly parallel to the pavement surface, and the acquired images are subject to distortion. Therefore, both intrinsic and extrinsic parameters of the cameras must be calibrated. The intrinsic parameters, which are model-dependent, were obtained via chessboard calibration, and image distortion was corrected, as shown in Figure 5a. The extrinsic parameters were calibrated using road markings of known dimensions. Specifically, four non-collinear points were selected at the vertices of two parallel lane markings, and their geometric correspondences were used to compute the transformation matrix, as shown in Figure 5b.

After calibration, pixel dimensions were converted into real-world measurements, enabling the computation of true lengths and areas of distress bounding regions. To ensure accuracy and consistency, the Computer Vision Annotation Tool (CVAT) was employed for manual annotation of bounding boxes closely aligned with distress boundaries. Some samples of three distress types are selected, and their calculated distress dimensions are summarized in Table 1. Field measurements of cracks and potholes confirmed that the relative errors between calculated and measured values were all below 10%.

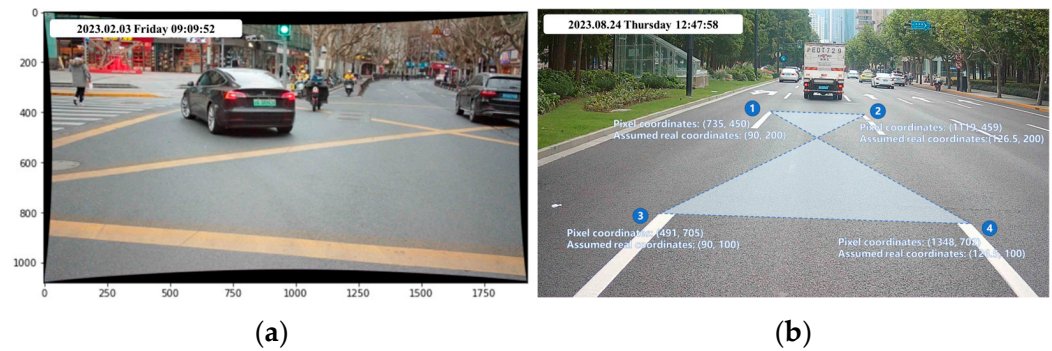


Figure 5. Camera parameter calibration. (a) Eliminating distortion caused by camera intrinsic parameters; (b) Selection of annotation points for camera extrinsic parameters calibrating.

Table 1. Calculation results of pavement distress dimensions.

Samples	Calculation Results	Measurement Results	Relative Error
Transverse crack sample 1	0.563	0.542	3.87%
Transverse crack sample 2	1.247	1.142	9.19%
Transverse crack sample 3	0.869	0.842	3.21%
Alligator crack sample 1	0.472	0.465	1.51%
Alligator crack sample 2	0.359	0.371	3.23%
Alligator crack sample 3	0.712	0.783	9.07%
Pothole sample 1	0.124	0.134	7.46%
Pothole sample 2	0.208	0.221	5.88%
Pothole sample 3	0.232	0.215	7.91%
Pothole sample 4	0.347	0.334	3.89%

Following these steps, tracking data of 164 pavement distresses were established for the period 1 January 2022–31 December 2023, comprising 38 transverse cracks, 57 alligator cracks, and 69 potholes, with a total of 9038 records. For transverse cracks, the longest crack measures 3.371 m, while the shortest measures 0.072 m. The dimensional range for alligator cracks spans from 0.191 m² to 1.83 m², and the dimensional range for potholes varies from 0.027 m² to 0.232 m². This tracking dataset can be acquired in previous study [40].

2.3. Multi-Factor Influences on Pavement Distress Deterioration

The deterioration of pavement distresses is jointly driven by multiple environmental factors, exhibiting significant lag effects and inherent uncertainty [28]. Considering the mechanisms and characteristics of different influencing factors, this study classifies them into two categories: inherent factors and environmental factors, with a total of twelve variables, as shown in Table 2. Inherent factors mainly include road-related attributes that remain stable over time for each distress instance. Their effects are long-term and continuous, providing a baseline influence on pavement performance. By contrast, environmental factors such as temperature, rainfall, and humidity are dynamic and vary over time. Their impacts typically manifest with a lag; for example, prolonged high temperatures, frequent rainfall, or sustained humidity fluctuations can accelerate pavement aging and deterioration, but such effects may only become evident after a certain delay. Thus, environmental factors exert stage-dependent and fluctuating impacts with complex time-lag characteristics.

Table 2. Multiple factors influencing pavement distress deterioration.

Type	Variable (Unit)	Data Source	Characteristics
Inherent factors	Road level	Municipal Administration Center of Xuhui District, Shanghai Baidu Map Open Platform	Constant baseline effects that do not change over time
	Road length (m)		
	Road age (year)		
	Traffic volume (vehicles/h)		
Environmental factors	Daily maximum temperature (°C)	Huiju Data Website	Nonlinear time-lag effects with dynamic changes
	Daily minimum temperature (°C)		
	Daily temperature difference (°C)		
	Daily rainfall (mm)		
	Daily humidity (%)		

The inherent factors are subdivided into road level, road length, road age, and traffic volume. Since all roadways in Xuhui District are asphalt pavements, the service life and design standards are closely linked to road level. Therefore, road level is used to represent structural differences. Moreover, traffic volume is strongly correlated with road level and design capacity, reflecting the functional attributes predetermined during planning and construction; hence, it is categorized as a road attribute factor. Although urban traffic volume fluctuates considerably within a day, showing “tidal characteristics”, the difference between weekdays and weekends is relatively small in terms of daily averages, making overall traffic volume highly stable. Accordingly, this study treats traffic volume as a constant variable. Real-time congestion indices and average speeds were retrieved from the Baidu Map Open Platform and combined with lane configuration data to estimate traffic volume for each road segment.

In contrast to these time-invariant inherent factors, environmental factors capture the time-lag impacts of weather conditions on pavement distress. Five variables were selected: daily maximum temperature, daily minimum temperature, daily temperature difference, daily rainfall, and daily humidity. Data were obtained from the Huiju Data platform (<https://hz.hjhj-e.com> (accessed on 2 June 2025)), covering meteorological observations in Xuhui District from January 2021 to December 2023, with a daily recording frequency. These records were used to calculate the five environmental factor variables employed in this study.

3. Methodology

To capture the time-lag effects of complex factors on pavement distress deterioration, convergent cross mapping was first employed to quantify the causal strength and lag days of environmental factors for three distress types. Building on this, a distress-level deterioration prediction model was developed by integrating an encoder–decoder framework with a long short-term memory (LSTM) network. The model embeds causal and time-lag characteristics and the constructed tracking dataset to enhance its ability to detect and predict abrupt deterioration inflection points. Moreover, Monte Carlo Dropout was introduced to characterize predictive uncertainty, enabling interval estimation of the prediction results.

3.1. Causal Analysis Based on Convergent Cross Mapping

Compared with the baseline effects of inherent factors, environmental factors such as temperature, rainfall, and humidity exert time-lag impacts on pavement performance. The influence of these environmental factors does not manifest immediately. Instead, it accumulates over time and progressively affects pavement performance. Considering that the deterioration processes of transverse cracks, alligator cracks, and potholes differ, environmental factors may impose distinct impacts on these three types of distresses. Therefore, this study adopts Convergent Cross Mapping (CCM) to investigate the nonlinear

lagged effects of environmental factors on each type of distress. Specifically, the CCM method is applied in two aspects: (i) quantifying the causal strength of environmental factors on pavement performance, where the causal strength would be incorporated as an additional feature weight in the input data; and (ii) revealing the time-lag effects of environmental factors on pavement deterioration, thereby identifying the number of lag days associated with each variable.

Convergent Cross Mapping, introduced by Sugihara et al. [41] in 2012, is a nonlinear method for detecting causality between time series. It can effectively capture nonlinear interactions in complex dynamic systems and is particularly suited for analyzing time-lag effects. The principle of CCM is that if X causally influences Y , the historical states of Y can be used to reconstruct the state space of X . The causal strength is then assessed by the correlation between the reconstructed state spaces, where a higher reliability of inferring X from Y indicates a stronger causal influence of X on Y .

The principle of CCM is illustrated in Figure 6. To identify the causal relationship between X and Y , the time series of each variable is first reconstructed into a state space, as shown in Figure 6a. Suppose $X(t)$ and $Y(t)$ represent two time series generated by projecting the dynamics of system M into a one-dimensional space, with length L , embedding dimension E , and time delay τ . The reconstructed state spaces at time t are expressed as $M_X = \{x(t)\}$ and $M_Y = \{y(t)\}$. Let $\hat{x}(t)|M_Y$ denotes the estimation of $X(t)$ obtained from M_Y via cross mapping. The procedure is as follows. First, the nearest neighbors of point $y(t)$ in M_Y is identified, and their corresponding indices as $y(t_1), y(t_2), \dots, y(t_{E+1})$ are recorded. These points correspond to the $E + 1$ nearest neighbors of $x(t)$ in M_X , denoted as $x'(t_1), x'(t_2), \dots, x'(t_{E+1})$. By applying this correspondence, the nearest neighbors of $x(t)$ in M_X can be determined. Subsequently, the local weighted average of these $E + 1$ points, which is $x'(t_i)$, is computed to estimate $x(t)$, thereby yielding the predicted value $\hat{x}(t)|M_Y$:

$$\hat{x}(t)|M_Y = \sum_{i=1}^{E+1} w_i x'(t_i) \quad (2)$$

$$w_i = u_i / \sum_{j=1}^{E+1} u_j \quad (3)$$

$$u_i = \exp\left(-\frac{\|y(t) - y(t_i)\|}{\|y(t) - y(t_1)\|}\right) \quad (4)$$

where w_i is the distance weight of the i -th nearest neighbor of $y(t)$ in M_Y , and $\| \cdot \|$ is the Euclidean distance between samples.

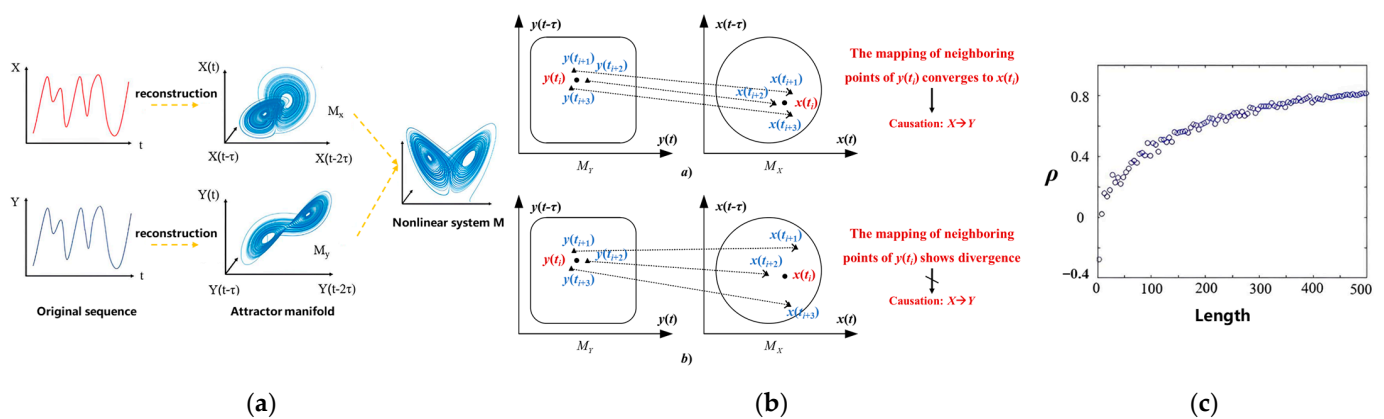


Figure 6. The principle of CCM method: (a) State space reconstruction; (b) Cross mapping; (c) Correlation coefficient calculation.

As illustrated in subgraph (a) of Figure 6b, if the sample point $y(t_i)$ in Y and its nearest neighbors are mapped onto X , and the corresponding neighboring points converge around $x(t_i)$, this indicates a causal relationship from X to Y . In contrast, as shown in subgraph (b) of Figure 6b, if the neighboring points $y(t_i)$ in Y show a scattered distribution after cross-mapping, it implies that no causal relationship exists from X to Y . The correlation coefficient ρ of $\hat{x}(t)|M_Y$ and $x(t)$ is calculated as follows:

$$\rho = \frac{\sum_{i=1}^L (x(i) - \overline{x(i)}) (\hat{x}(i)|M_Y - \overline{\hat{x}(i)|M_Y})}{\sqrt{\sum_{i=1}^L (x(i) - \overline{x(i)})^2 \sum_{i=1}^L (\hat{x}(i)|M_Y - \overline{\hat{x}(i)|M_Y})^2}} \quad (5)$$

If X serves as a driving factor for Y , then when predicting X through the reconstructed state space M_Y , the estimated value $\hat{x}(t)|M_Y$ will gradually converge toward $x(t)$ as the length of the time series L increases. Correspondingly, the correlation coefficient ρ will increase and eventually stabilize. As illustrated in Figure 6c, the ρ converges to approximately 0.8, which indicates the presence of a causal relationship from X to Y . It should be noted that the ρ in the CCM algorithm differs from conventional statistical correlation coefficients. Here, ρ reflects the degree of cross mapping convergence between reconstructed state spaces, and thus represents the strength of the causal relationship [42], with values ranging between [0, 1]. Specifically, a value of zero indicates the absence of causality between variables, while a value closer to one implies stronger causal dependence. Therefore, the converged ρ value can be used as an indicator to quantify the causal strength, providing a basis for evaluating the causal relationship between environmental factors and pavement distresses deterioration.

3.2. Distress-Level Deterioration Prediction Model

In recent years, deep learning-based pavement deterioration prediction algorithms have demonstrated significant advantages in improving prediction accuracy. However, such methods can usually only provide a single point estimation. It means that they can only output a fixed value as the prediction result but cannot provide the interval distribution to reflect the uncertainty contained in the prediction results. When pavement distress deterioration is influenced by multiple complex factors, the predictive model becomes susceptible to variable perturbations and stochastic noise, thereby reducing the reliability of point estimation and constraining their applicability and reference value in maintenance decision-making. Therefore, for prediction tasks, it is essential not only to compute deterministic prediction values but also to quantify predictive uncertainty through interval distribution estimation. This approach mitigates the randomness and unreliability of single prediction outputs, providing more robust support and guidance for pavement maintenance decisions.

Bayesian Neural Networks (BNNs) provide a mathematically grounded framework for inferring the probability distribution of model outputs [43]. By constructing a posterior distribution, this method mitigates the impact of stochastic fluctuations during training and enhances the model's generalization capability. Moreover, since the model outputs a distribution rather than a single value, it enables interval estimation of predictions, thereby expressing uncertainty. Monte Carlo Dropout (MC Dropout) is an efficient approximate Bayesian inference technique for quantifying predictive uncertainty in neural networks. During the prediction phase, MC Dropout randomly drops neurons multiple times, thereby producing multiple different inference paths and generating a series of prediction outcomes. The final prediction is obtained by averaging these outputs, while their distributional characteristics are used to assess predictive uncertainty and estimate confidence intervals.

Gal et al. [43] formally demonstrated that a neural network employing Dropout is mathematically equivalent to performing variational inference over the network parameters. It identifies a simple and tractable approximate distribution $q_\theta(W)$ from a manageable family of distributions, such that the Kullback–Leibler (KL) divergence between the approximate distribution and the true posterior distribution of the model parameters is minimized:

$$\mathcal{L}(\theta, p) = -\frac{1}{N} \sum_{i=1}^N \log p(y_i | f^{\hat{W}_i}(x_i)) + \frac{1-p}{2N} \|\theta\|^2 \quad (6)$$

where the first term represents the negative log-likelihood, while the second term corresponds to the regularization parameter. N is the number of data points, p is the dropout rate, $\hat{W}_i \sim q_\theta^*(W)$. And $q_\theta^*(W)$ represents the minimum value of this optimization objective. In regression tasks, the likelihood is typically assumed to follow a Gaussian distribution, in which case the negative log-likelihood can be expressed as follows:

$$-\log p(y_i | f^{\hat{W}_i}(x_i)) \propto \frac{1}{2\sigma^2} \|y_i - f^{\hat{W}_i}(x_i)\|^2 + \frac{1}{2} \log \sigma^2 \quad (7)$$

σ represents the noise in the model output, which to some extent reflects the degree of uncertainty in the prediction. To capture the probabilistic distribution of the model results, the prediction is conducted T times during testing. The average of results of T times is taken as the final predicted value, while the results of T times constitute an interval distribution estimation of predicted values.

$$E(y) \approx \frac{1}{T} \sum_{t=1}^T f^{\hat{W}_t}(x) \quad (8)$$

$$Var(y) \approx \sigma^2 + \frac{1}{T} \sum_{t=1}^T f^{\hat{W}_t}(x)^T f^{\hat{W}_t}(x_t) - E(y)^T E(y) \quad (9)$$

The MC Dropout-based uncertainty analysis method requires no modification to the existing neural network architecture. Instead, it approximates the Bayesian posterior through repeated forward passes during inference. This approach preserves the expressive capacity of deep models for high-dimensional, large-scale datasets while providing a more comprehensive characterization of predictive distributions and uncertainty quantification. Consequently, it demonstrates superior scalability and practicality for applications such as pavement distress prediction, which involve large data volumes and high-dimensional features, outperforming other uncertainty-aware approaches in both flexibility and ease of implementation.

In Section 3.1, the time-lag effect of environmental factors on the pavement distress deterioration is characterized using the CCM method, and the causal strength and corresponding lag days are obtained. To enhance the model's capability to identify and predict the inflection points of deterioration mutations, the causal and time-lag characteristics are fused with embedded features extracted by the encoder–decoder model. Subsequently, the MC Dropout is incorporated to approximate Bayesian inference during the prediction process, leading to the development of a BayesLSTM short-term deterioration prediction model that accounts for uncertainty. This model not only produces point estimation but also provides interval estimation, thereby enabling the quantification of prediction uncertainty. By alleviating the randomness inherent in single-point predictions under complex external disturbances, this approach effectively enhances the robustness and reliability of prediction results.

Following the studies of Uber [44], Srivastava [45], and Ardestani [46] the proposed model in this study comprises two main components: an encoder–decoder model and a prediction network. The encoder–decoder is designed to extract high-dimensional features from the time series, reconstruct the input, and output the learned embedded features. To ensure that the encoder can capture representative high-dimensional features, a pre-training operation is required. During the pre-training process, the decoder is employed to reconstruct the encoder’s extracted features into predicted values, which are then compared with the corresponding true values. The resulting errors are used to update the parameters of encoder–decoder model, thereby yielding a well-trained encoder with strong feature extraction capability.

The network structure of the encoder is illustrated in Figure 7a, where an example input with a shape of $(1, T, 1)$ is presented. The first LSTM layer, consisting of 32 hidden units, is employed for automatic feature extraction, producing an output with the shape $(1, T, 32)$. This output is subsequently passed through a dropout layer, which randomly sets a portion of the weights to zero. This operation is represented by the dashed lines in the figure. The second LSTM layer, comprising 7 hidden units, is responsible for encoding features. It takes the dropout output as input, and the last unit’s output serves as the layer’s results, yielding a vector of shape $(1, 7)$. This vector, referred to as the embedded features, constitutes part of the encoder’s output. Further, to make the encoder output compatible with the decoder, the vector must be transformed into a 3D structure. This is achieved using a RepeatVector() layer, which replicates the vector and produces an output with the shape $(1, T, 7)$, as shown in Figure 7b. Through this operation, the encoder can effectively capture anomalies in the input data and convey them to the prediction network via the learned embedded features, thereby enhancing the overall prediction accuracy.

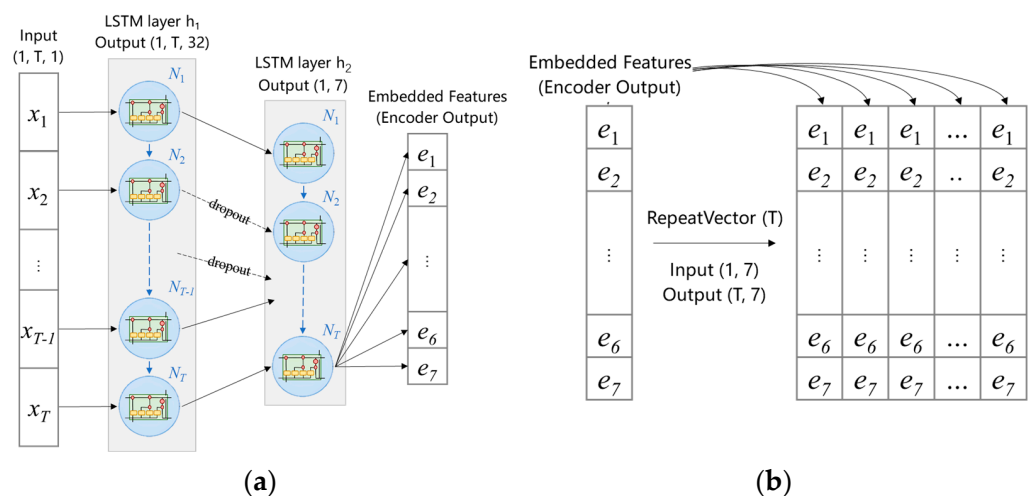


Figure 7. Structure and output processing of encoder model. (a) Encoder model; (b) Connecting encoder to decoder using RepeatVector() layer.

Figure 8a shows the network structure of decoder. In contrast to the encoder, the function of decoder is to process and reconstruct the information derived from the encoder’s output. The accuracy of the reconstructed results is directly determined by the encoder’s feature extraction capability. To ensure the encoder performs effectively, it should be sufficiently trained. Accordingly, the decoder is employed to evaluate the encoder’s ability to extract features. By reconstructing the features produced by the encoder and comparing them with the original input data, the decoder provides a means to compute reconstruction loss, which in turn directs the encoder’s training and convergence. The first LSTM layer in the decoder is used to restore features, consisting of 32 hidden units. For the feature data received from the encoder with the shape $(1, T, 7)$, this layer produces an output of

shape $(1, T, 32)$. The second LSTM layer, containing 7 hidden units, is used to generate the final outputs. It takes the dropout-modified outputs as input and produces results with the shape $(1, T, 1)$. During the pre-training process, the input time-series data are first encoded to obtain their feature representation, which are subsequently decoded and reconstructed by the decoder to generate the restored time series. The difference between the original and reconstructed sequences is then computed as the loss function, which is minimized through backpropagation to continuously optimize the parameters of the encoder–decoder model. This process ensures that the reconstructed sequences approximate the original data as closely as possible. After sufficient training, the encoder–decoder model can extract features that effectively represent the key information in the original time-series data, thereby providing high-quality inputs for subsequent prediction. The temporal embedded features extracted are then used as the primary input to the prediction network. Furthermore, to enhance the model's ability to capture environmental driving mechanisms, the causal strength of environmental factors is introduced. These causal characteristics are concatenated with embedded features to form an enhanced input representation, which serves as the final input to the prediction network.

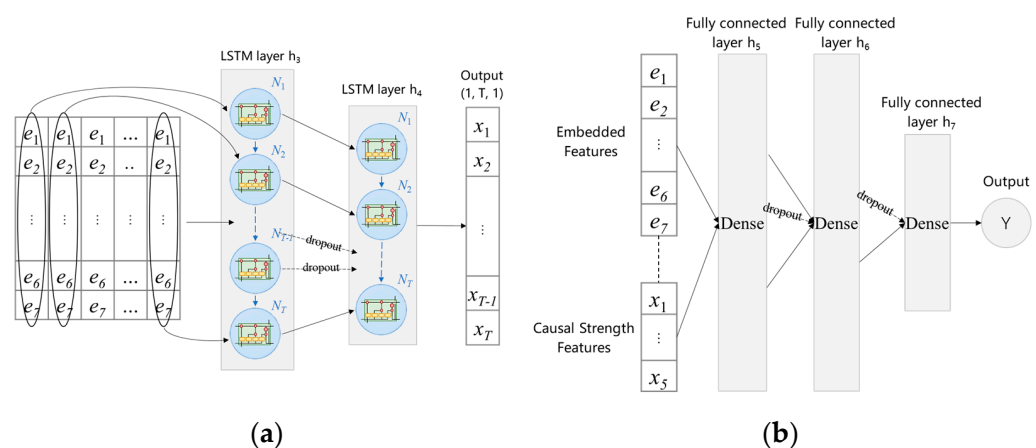


Figure 8. Structure of encoder model and prediction network. (a) Decoder model; (b) Prediction network.

The prediction network is composed of three fully connected layers, with dropout layers applied after the first two layers. The final fully connected layer is responsible for generating the prediction output. During model training, dropout is applied to randomly deactivate neurons in the hidden layers, which helps prevent the model from overfitting to the training set and enhances its generalization capability for unseen data. Conventionally, dropout is disabled during the prediction phase of neural networks to ensure stability and determinism, resulting in a single fixed prediction output. However, in this study, the MC Dropout method is employed, wherein dropout remains active during prediction. This ensures that the network structure varies across different prediction passes, thereby producing multiple prediction outcomes. By performing statistical analysis on these outcomes, the mean and standard deviation of predicted values can be computed, allowing the construction of an approximate probability distribution of the predictive results. The structure of the prediction network is illustrated in Figure 8b.

4. Experiment

4.1. Analysis Results of Causal and Time-Lag Characteristics

Analysis of causal and time-lag characteristics based on the CCM method is conducted in three steps. First, the optimal embedding dimension E for the reconstructed state space is determined. Second, the applicability of the CCM method to the given dataset is evaluated.

Finally, the lag time and correlation coefficients are computed to quantify the time-lag days and the causal strength of each causal factor.

4.1.1. Determination of Nonlinear Spatial Parameters

Reconstructing the phase space requires determining both the embedding dimension E and the time-delay vector τ . The selection of τ is generally based on empirical values. A smaller time-delay vector results in higher resolution of the cross mapping and improved accuracy of the causal inference. To ensure the reliability of the shadow manifold construction and the resolution of the cross mapping, this study adopts the minimal time-delay vector, which means $\tau = 1$, thereby maximizing the preservation of system dynamics and enhancing the accuracy of causal detection [46]. The embedding dimension E reflects how many past observations are required to effectively predict future states. The optimal embedding dimension is defined as the dimension that minimizes the mean absolute error between observed and predicted values. The choice of E is influenced by several factors, including system complexity, time-series length, and noise level. An excessively large E may introduce redundant information into the reconstructed space and increase computational complexity, whereas an overly small E may fail to capture sufficient information from the original system. To address this issue, the Simplex Projection method is employed to evaluate predictive performance under different embedding dimensions, and the dimension that achieves the best predictive accuracy is selected as the final embedding dimension. Simplex Projection is a nearest-neighbor-based algorithm that predicts future trajectories by referencing past events with similar dynamics.

Considering the distinct deterioration processes of transverse cracks, alligator cracks, and potholes, this study employs the open-source pyEDM package developed by Sugihara's team (<https://github.com/SugiharaLab/pyEDM> (accessed on 21 June 2025)) to determine the optimal embedding dimension for five environmental factors corresponding to each distress type. During computation, the parameter setting specifies a time-delay vector of $\tau = 1$. The results are presented in Figure 9a–c.

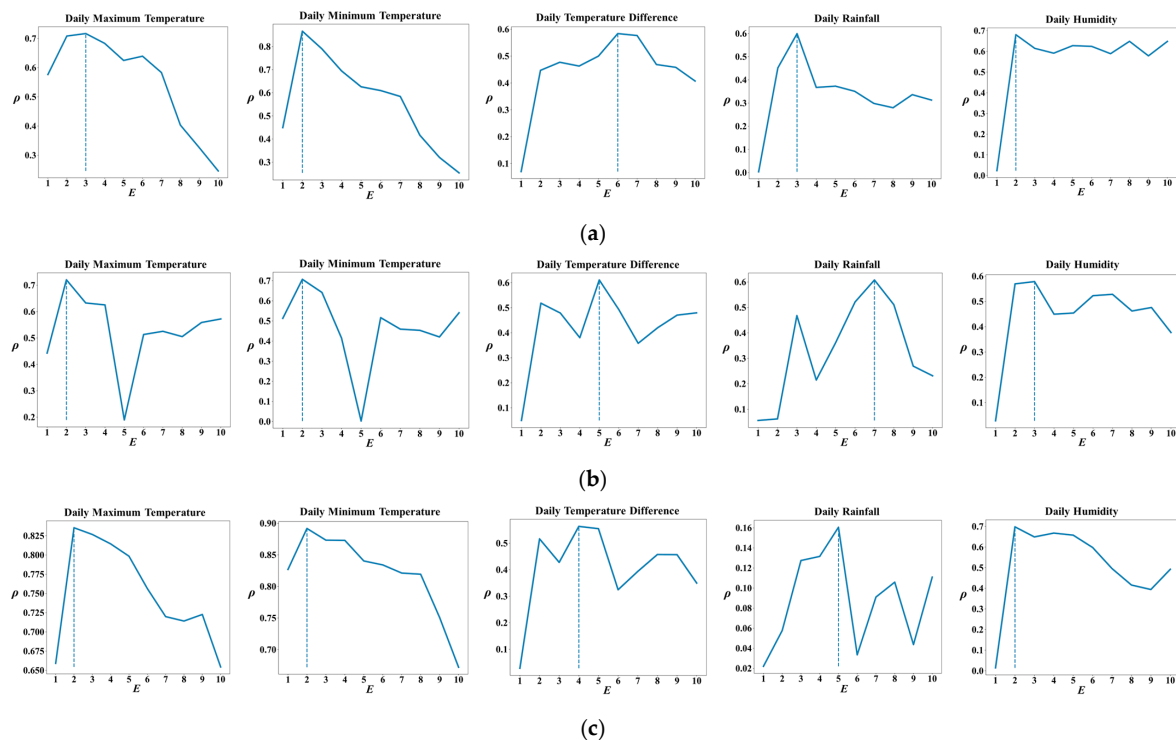


Figure 9. Changes in the embedding dimension of environmental factors: (a) Transverse crack; (b) Alligator crack; (c) Pothole.

The above figure shows the selection process of the optimal embedding dimension for the five environmental factors across three distress types. The vertical axis ρ represents predictive ability, and the embedding dimension E corresponding to the maximum ρ value is identified as the optimal embedding dimension. Each factor exhibits a distinct optimal embedding dimension. As shown in Figure 9a, for transverse crack, the five variables reach their maximum ρ values at $E = 3, 2, 6, 3, 2$, respectively. It means that the optimal embedding dimensions of the five variables are 3, 2, 6, 3, 2. The same approach applies to alligator cracking and potholes, and the results of the optimal embedding dimensions are summarized in Table 3.

Table 3. Optimal embedding dimension.

	Daily Maximum Temperature	Daily Minimum Temperature	Daily Temperature Difference	Daily Rainfall	Daily Humidity
Transverse crack	3	2	6	3	2
Alligator crack	2	2	5	7	3
Pothole	2	2	4	5	2

4.1.2. Nonlinearity and Random Noise Tests

CCM method is a powerful tool that has been widely applied to identify interactions among variables in weakly coupled, non-random, and nonlinear systems. However, for nonlinear systems that are not entirely stochastic, the prediction error typically increases with longer forecasting horizons when historical data are used to infer future values. Therefore, before conducting causal relationship analysis, it is necessary to verify whether the variables are affected by random noise.

Based on the optimal embedding dimension E obtained in the previous section, the prediction step was gradually varied from 1 to 10. The corresponding changes in prediction ability were then examined to assess the nonlinearity and noise of each variable. The results are presented in Figure 10a–c. It can be observed that for all three distress types, the prediction ability of environmental factors declines as the prediction step increases. Although slight improvements are observed at some steps, the overall trend indicates a decrease in prediction ability with increasing prediction steps. This finding suggests the presence of nonlinearity, implying that the deterioration processes of transverse cracks, alligator cracks, and potholes in relation to environmental factors constitute a nonlinear system rather than a completely stochastic one.

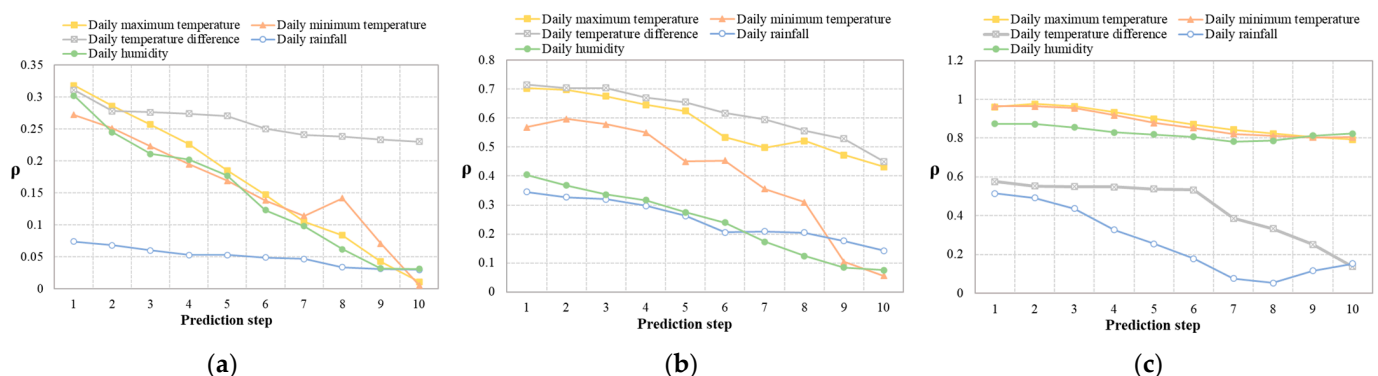


Figure 10. Changes in prediction ability with prediction steps: (a) Transverse crack; (b) Alligator crack; (c) Pothole.

4.1.3. Calculation of Lag Days and Correlation Coefficients

After determining the parameters of the reconstructed phase space and completing the tests for nonlinear characteristics and random noise, this study applied the CCM method to

quantify the lag days and correlation coefficients between five environmental factors and the deterioration of three distress types.

Specifically, the five environmental factors were defined as variable X , while the distress dimensions were defined as variable Y . By modifying the lag parameter Tp in the CCM function, the correlation coefficients under different lag steps were calculated. Here, $Tp = -1$ denotes a lag of one step, which corresponds to three days in this study. So the lag days d is $d = 3 \times Tp$. The lag step Tp at which the correlation coefficient ρ reaches its maximum is considered the lag step of factor X , while the maximum value of ρ itself represents the causal strength between the environmental factor and pavement distress deterioration.

Figure 11 presents the causal relationship test results between transverse crack deterioration and the five environmental factors. Figure 11a illustrates the variation in correlation coefficients under different lag steps. It can be observed that the maximum correlation coefficients are attained at lag steps of -8 , -9 , -7 , -9 , and -5 , corresponding to lag times of 24, 27, 21, 27, and 15 days, respectively. In the subsequent analysis, the lag step Tp was set to the optimal value for each factor, and the convergence of cross-mapping predictive power with increasing time series L was examined, as shown in Figure 11b. The results indicate that the correlation coefficients of daily maximum temperature, daily minimum temperature, and daily rainfall gradually converge to peak values of 0.877, 0.922, and 0.236, respectively, with p -values < 0.01 . This demonstrates that, at the 1% significance level, these three factors exhibit statistically significant causal relationships with transverse crack deterioration. The causal strength is represented by the converged correlation coefficient. In contrast, the correlation coefficient of daily temperature difference does not exhibit convergence with increasing L . And its p -value, which is 0.1524 (> 0.01) is not significant at the 10%, 5%, or 1% levels. Similarly, although the correlation coefficient of daily humidity shows a convergence trend, its p -value, which is 0.5813 (> 0.01) indicates no significant causal relationship with transverse crack deterioration.

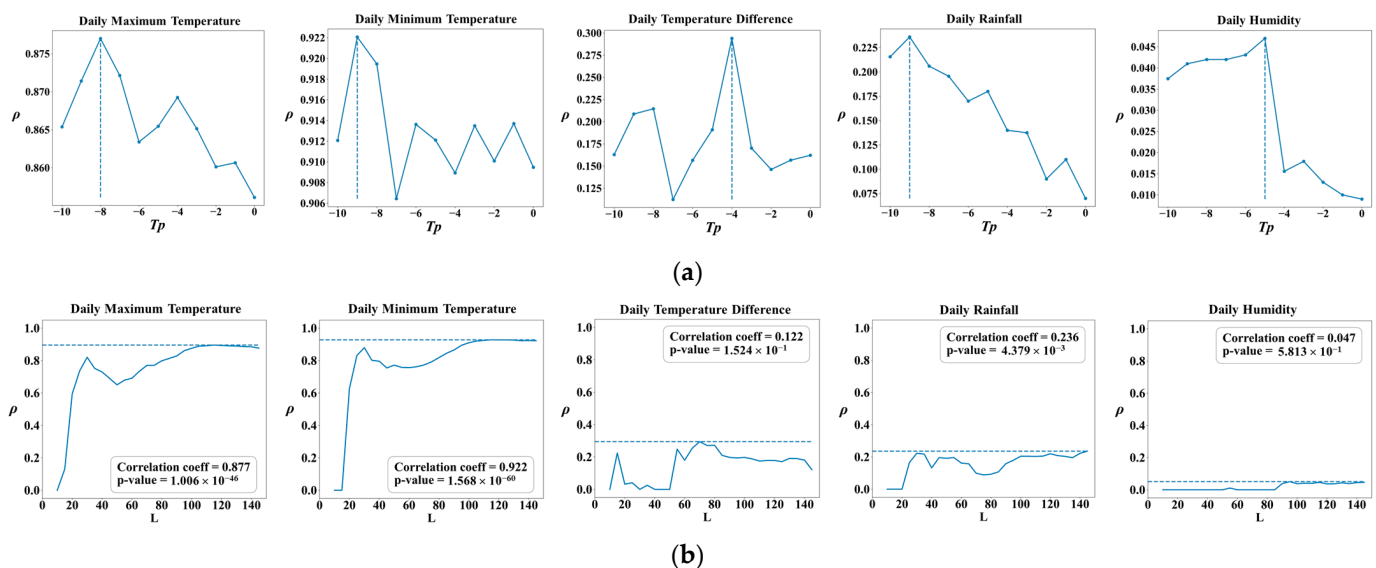


Figure 11. Causality test results between transverse crack deterioration and five environmental factors: (a) Lag steps; (b) Causal strength.

Similarly, the causal relationship test results between the five environmental factors and the deterioration of alligator cracks and potholes are presented in Figures 12 and 13. Among them, subgraph (a) depicts the variation trends of correlation coefficients with respect to different lag steps, where the lag step corresponding to the maximum coefficient

is identified as the optimal lag. And subgraph (b) illustrates the causal test results under the optimal embedding dimension and lag step settings. It can be seen that the optimal lag steps of the five environmental factors for alligator cracks are -7 , -3 , -7 , -1 , and -5 , with converged correlation coefficients of 0.902, 0.931, 0.305, 0.379, and 0.032, respectively. For potholes, the optimal lag steps are -2 , -3 , -5 , -3 , and -5 , with converged correlation coefficients of 0.919, 0.953, 0.202, 0.427, and 0.023, respectively. The results reveal that daily maximum temperature, daily minimum temperature and daily temperature difference exhibit significant causal relationships with the deterioration of both alligator cracks and potholes, whereas the causal influence of daily humidity is not statistically significant.

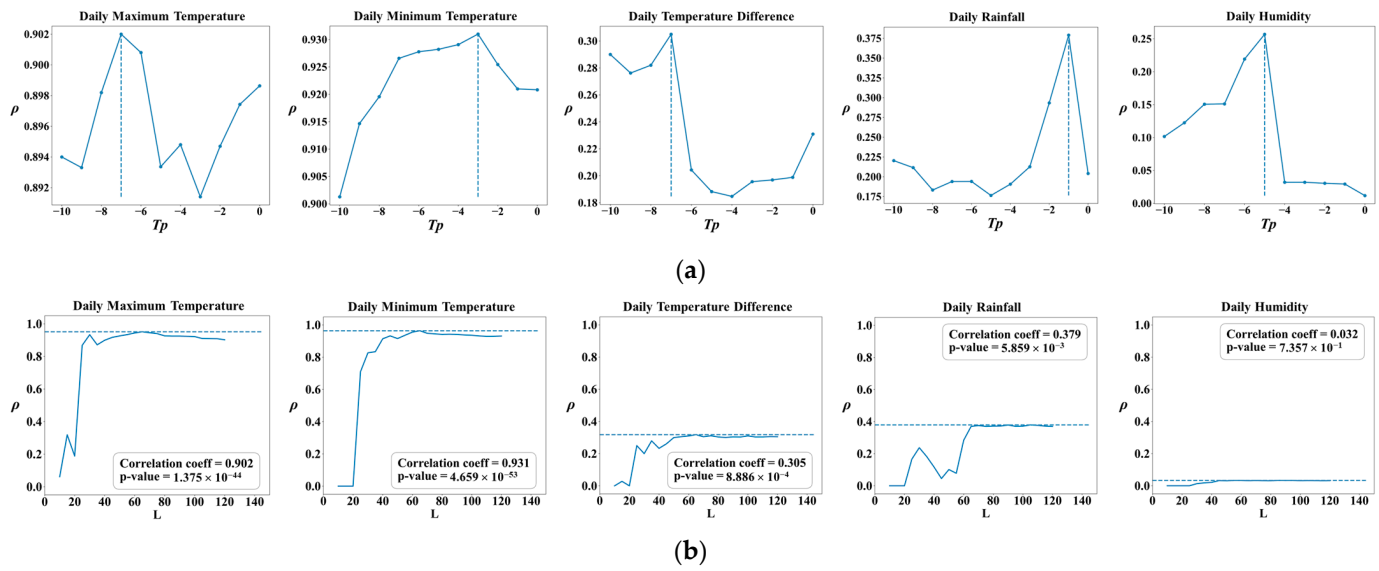


Figure 12. Causality test results between alligator crack deterioration and five environmental factors: (a) Lag steps; (b) Causal strength.

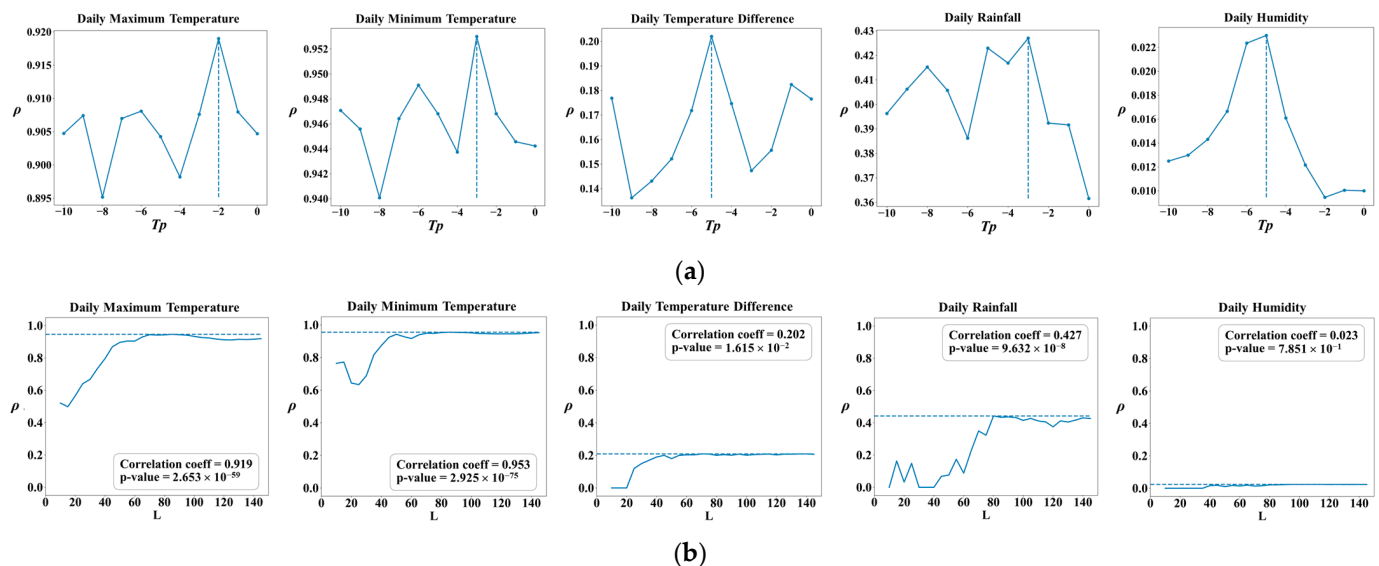


Figure 13. Causality test results between pothole deterioration and five environmental factors: (a) Lag steps; (b) Causal strength.

In summary, the causal strength and lag days of the five environmental factors on three distress types are presented in Table 4. Except for daily temperature difference, the causal strengths of daily maximum temperature, daily minimum temperature, and daily rainfall on the deterioration of three distress types exhibit an increasing trend. It

indicates that the influence of environmental factors progressively intensifies across the three distress types. This may be due to the fact that, during the early stages of distress development, temperature plays a more prominent role in the deterioration process. As the distress gradually expands and worsens, the impact of environmental factors becomes more pronounced. Prolonged changes in humidity can lead to moisture infiltration into cracks, further accelerating their expansion, thereby enhancing the role of environmental factors in deepening cracks and expanding potholes.

Table 4. Causal intensity and lagging days results of environmental factors.

		Transverse Crack	Alligator Crack	Pothole
Daily Maximum Temperature	Causal strength	0.877	0.902	0.919
	Lag days	24	21	6
Daily Minimum Temperature	Causal strength	0.922	0.931	0.953
	Lag days	27	9	9
Daily Temperature Difference	Causal strength	\	0.305	0.202
	Lag days	\	21	15
Daily Rainfall	Causal strength	0.236	0.379	0.427
	Lag days	27	3	9
Daily Humidity	Causal strength	\	\	\
	Lag days	\	\	\

In terms of lag days, daily rainfall shows the shortest lag effect on alligator crack, with 3 days, while daily maximum temperature exhibits a lag of 6 days on pothole deterioration. This suggests that alligator crack is more susceptible to the immediate impacts of rainfall, whereas pothole deterioration is more strongly influenced by short-term temperature variations. This difference likely arises from the distinct mechanisms through which environmental factors affect these two types of distresses, leading to varying responses to rainfall and temperature changes. Moisture infiltration accelerates the expansion of alligator cracks, making it one of their primary deterioration mechanisms. In addition, temperature fluctuations cause the freezing and thawing of water, which exacerbates the deterioration process of potholes. By contrast, the lag effects of environmental factors on transverse crack are more pronounced, with generally longer lag durations. The results in Table 4 will serve as additional features and will be incorporated into the uncertainty analysis in the following section.

4.2. Distress-Level Deterioration Prediction Results

Based on the constructed high-frequency tracking dataset, the performance of proposed BayesLSTM prediction model was evaluated. For the three distress types, the prediction of distress dimensions was conducted using the factors defined in Section 2.3. Furthermore, the causal strength and lag days obtained in Section 4.1 (Table 4) were incorporated as additional features to further enhance predictive capability. In terms of input data construction, causal strength was introduced as an auxiliary feature for each variable, adding an additional dimension to the input at each time step to represent the causal intensity of the environmental factors. Considering that the maximum lag was 27 days, the length of the input time series needed to exceed this threshold. Accordingly, the time window was set to 30 days, meaning that the distress dimension on day 31 was predicted based on the preceding 30 days of historical data. To account for lag effects, the historical data of each variable corresponding to its specific lag day was also incorporated into the input sequence.

Using two years of high-frequency tracking dataset, continuous deterioration sequences were first fed into an encoder for feature extraction, with the extracted features

reconstructed by a decoder to pre-train the encoder's representation capability. During the prediction network training, the encoder parameters were frozen, and only the fully connected layers were optimized. According to relevant studies [47], for pretraining, the first 19 months of data were used for training and the following 5 months for validation. For the prediction network, the first 18 months were used for training, 2 months for validation, and the last 4 months for testing, which yielded the minimum MAE (Mean Absolute Error). In the training process, 20% of the training data were reserved for cross-validation. A sliding window of 30 days was adopted (step size = 1), predicting the distress dimension on day 31 from the previous 30 days of history. The model was implemented in PyTorch 2.8.0 under Ubuntu 20.04.3 with Python 3.6, running on an Intel 128-core CPU, 256 GB RAM, and an NVIDIA GeForce RTX 4090 GPU (24 GB memory). ReLU was chosen as the activation function, Adam as the optimizer, and mean squared error (MSE) as the loss function, computed as in Formula (10). Referring to related studies [46,47], the hyper-parameters settings are shown in Table 5. The BayesLSTM model was trained by combining different hyper-parameter values. Through model training and tuning, the optimal combination of parameters is obtained.

$$MSE = \sum_{i=1}^N \frac{1}{N} (y_i - \hat{y}_i)^2 \quad (10)$$

Table 5. Hyper-parameters settings.

Parameters	Combinations	Optimal Values
Learning rates	0.001, 0.01, 0.1	0.01
Dropout rates	0, 0.1, 0.14, 0.27, 0.36, 0.41, 0.5	0.1
LSTM layer h ₁ size	32, 50, 128	128
LSTM layer h ₂ size	7, 14, 20, 25, 28	14
LSTM layer h ₃ size	128, 64, 28	128
LSTM layer h ₄ size	64, 32, 14	32
Dense layer h ₅ size	50, 7	7
Dense layer h ₆ size	7	7
Dense layer h ₇ size	1	1

The loss function curves during encoder–decoder pretraining are shown in Figure 14a,b. As training epochs increased, both training and validation losses consistently decreased, indicating progressive improvements in feature extraction and sequence reconstruction. After 200 epochs, the loss stabilized and converged, at which point training was terminated and the parameters were saved as pretrained weights. Figure 14c illustrates the reconstruction performance. The pretrained encoder extracted features from continuous time series, which were then reconstructed by the decoder. The reconstructed sequences closely matched the original data, demonstrating that the extracted features effectively captured the underlying temporal information.

After pretraining the encoder, its parameters were frozen, and the prediction network was trained. The converged parameters were then saved as the final weights of the prediction model. During inference, dropout remained active with the same rate as in training, randomly deactivating neurons to generate multiple predictions rather than a single deterministic estimate. This yielded an approximate posterior distribution of a Bayesian neural network, enabling uncertainty quantification by extending point estimation to interval estimation. Figure 15 compares interval and point predictions for three distress types. The gray regions and blue curves represent predictive intervals, while red lines denote the truth value. The results show that prediction intervals followed an approximately normal distribution, and the predictive means closely matched the observed values, confirming both accuracy and reliability of the uncertainty-aware framework.

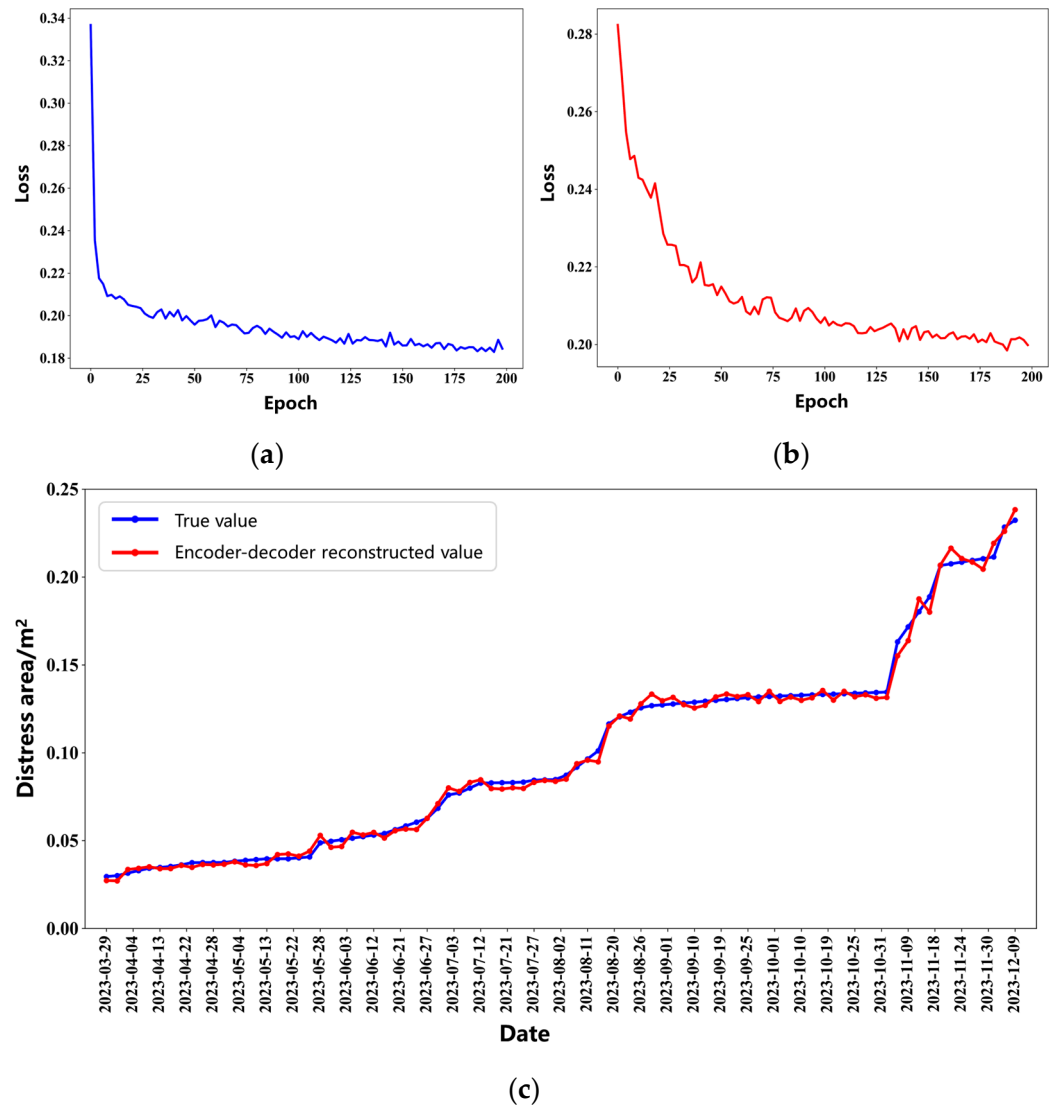


Figure 14. Pre-Training of encoder-decoder model. (a) Training loss; (b) Validation loss; (c) Output.

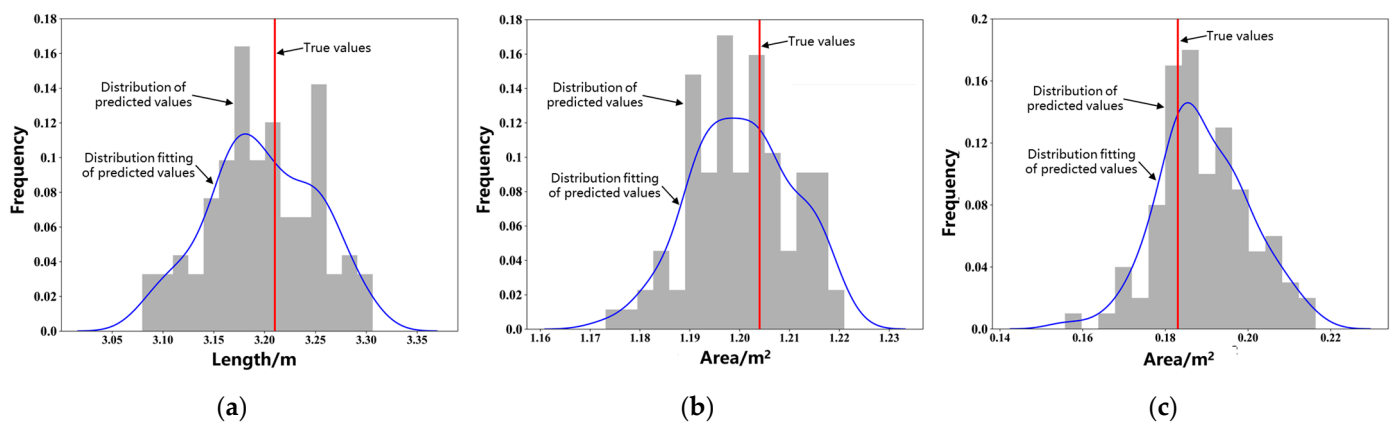


Figure 15. Comparison between interval estimation and point estimation. (a) Transverse crack; (b) Alligator crack; (c) Pothole.

Figure 16 presents the deterioration predictions of three pavement distresses based on the proposed prediction network. The blue curve denotes the true values, the red curve denotes the predicted values, and the yellow band denotes the 95% confidence interval. Overall, the predicted trajectories align well with the actual deterioration trends, demonstrating strong predictive capability of the model. Among the three distresses, the

predictions for alligator cracks and potholes fit more closely, while those for transverse cracks are less accurate, likely due to the smaller sample size limiting feature learning during training. This may also stem from the fact that the deterioration of transverse cracks exhibits higher variability. Its propagation is typically non-uniform, often manifesting as sudden localized expansions or severe changes due to localized stress concentrations. Moreover, factors such as humidity, temperature variations, and traffic loads tend to have significant fluctuations in their impact on transverse cracks. The various interactions increase the complexity of predicting transverse crack deterioration.

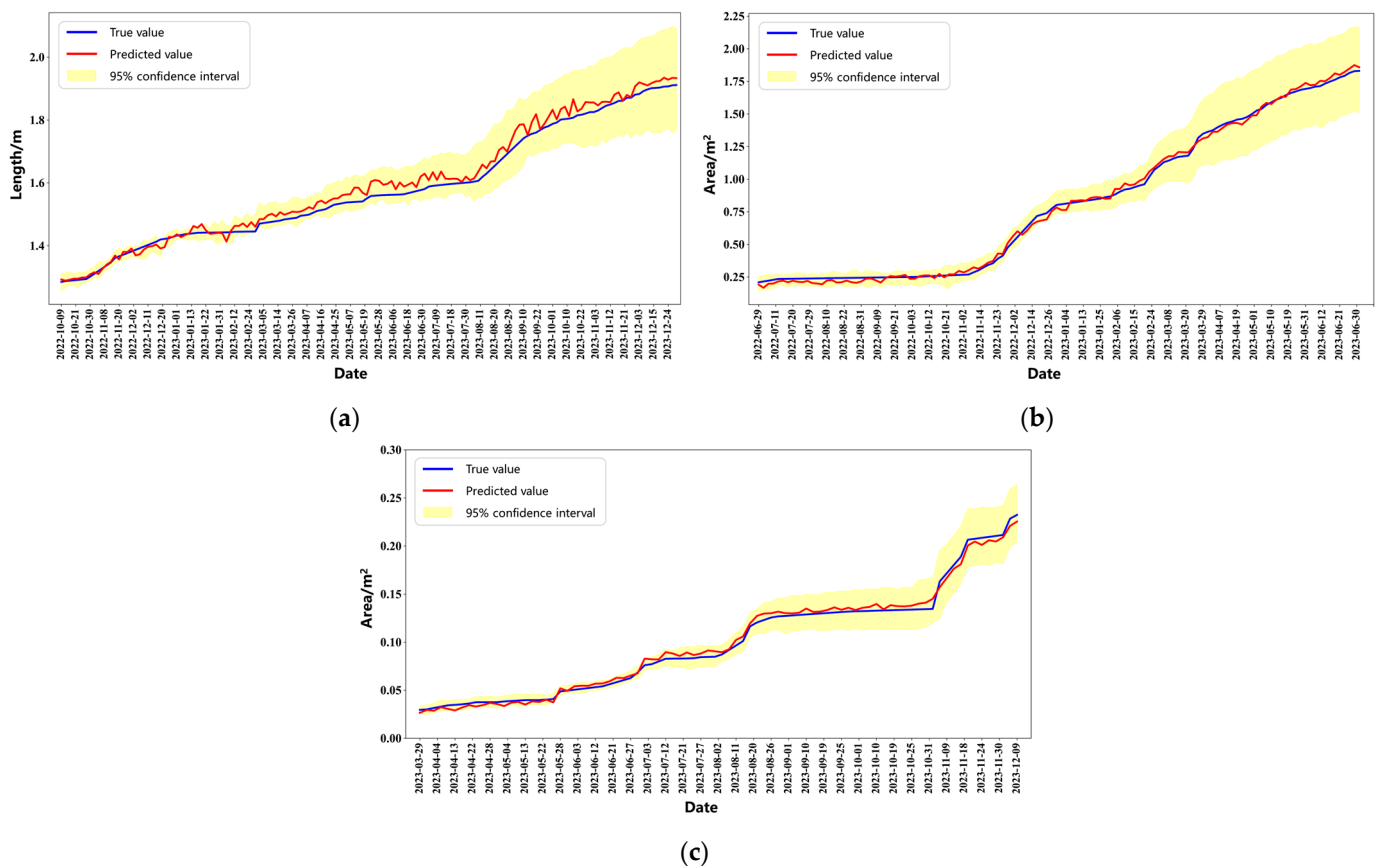


Figure 16. Deterioration prediction results of three types of pavement distress. (a) Transverse crack; (b) Alligator crack; (c) Pothole.

Moreover, the confidence intervals gradually widen over time, indicating higher predictive accuracy and narrower uncertainty bands in the early stages of deterioration. As prediction steps extend, accumulated errors lead to broader intervals. Notably, moments of sharp widening often coincide with abrupt deterioration shifts, suggesting that sudden transitions introduce greater uncertainty and expand the prediction intervals. From a maintenance decision-making perspective, this growing uncertainty suggests that decision-makers need to adopt a more cautious approach when formulating long-term maintenance plans, particularly for areas or distress types with higher levels of uncertainty. It is essential to periodically reassess pavement conditions and repair priorities to avoid making overly aggressive long-term repair decisions based on uncertain predictions, ensuring the efficient allocation of maintenance resources and the sustainable performance of the pavement.

4.3. Evaluation of Interval Estimation

Model prediction performance was evaluated using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), as defined in Formulas (11) and (12). MAE measures absolute deviations, while MAPE emphasizes relative errors.

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (11)$$

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (12)$$

where $\hat{y}_i$ is the predicted value, y is the true value, and N is the sample numbers.

In addition, given that the model produces interval forecasts, Prediction Interval Coverage Probability (PICP) and Mean Prediction Interval Width (MPIW) [48] were adopted to evaluate interval prediction performance. PICP assesses the reliability of prediction intervals, with higher values indicating stronger coverage of true values and thus greater prediction reliability, as defined in Formulas (13) and (14).

$$PICP = \frac{1}{n} \sum_{i=1}^N Det_i \quad (13)$$

$$Det_i = \begin{cases} 1, & L_i \leq area_i \leq H_i \\ 0, & otherwise \end{cases} \quad (14)$$

where n is sample numbers, Det_i indicates whether the true value $area_i$ falls within the prediction interval, as shown in Formula (14). L_i and H_i represent the upper and lower bounds of the predicted value for each sample i .

MPIW quantifies the width of prediction intervals, with smaller values indicating lower dispersion and more precise interval estimation. To eliminate the influence of varying sample scales on MPIW, the normalized MPIW (NMPIW) is further employed, representing the proportion of the prediction interval width relative to the overall value range, as shown in Formulas (15) and (16).

$$MPIW = \frac{1}{n} \sum_{i=1}^N (H_i - L_i) \quad (15)$$

$$NMPIW = MPIW / (\max(area_i) - \min(area_i)) \quad (16)$$

Generally, PICP and NMPIW exhibit a trade-off. A higher PICP indicates stronger interval coverage but often results in wider prediction intervals and increasing NMPIW. Therefore, in practice, it is essential first to ensure that PICP meets the desired coverage level, and then to minimize the interval width to achieve a balance between prediction reliability and precision.

To evaluate the performance of the proposed algorithm in interval prediction, three models, which are standard LSTM, the proposed BayesLSTM, and BayesLSTM without causal and time-lag characteristics, were tested for three distress types. Prediction performance was compared using four metrics: MAE, MAPE, PICP, and NMPIW. This analysis systematically assesses the overall improvement in prediction accuracy and interval estimation capability brought by incorporating causal and time-lag characteristics and the BayesLSTM structure. The comparative results are presented in Tables 6–8.

Table 6. Comparison results of transverse crack prediction.

Model	MAE	MAPE	PICP	NMPIW
LSTM	0.114	1.037	\	\
BayesLSTM with causal and time-lag characteristics	0.0201	0.0125	100%	0.131
BayesLSTM without causal and time-lag characteristics	0.072	0.658	80.6%	0.613

Table 7. Comparison results of alligator crack prediction.

Model	MAE	MAPE	PICP	NMPIW
LSTM	0.0587	0.426	\	\
BayesLSTM with causal and time-lag characteristics	0.0241	0.049	100%	0.287
BayesLSTM without causal and time-lag characteristics	0.043	0.306	87.8%	0.427

Table 8. Comparison results of pothole prediction.

Model	MAE	MAPE	PICP	NMPIW
LSTM	0.028	0.276	\	\
BayesLSTM with causal and time-lag characteristics	0.0039	0.0467	100%	0.026
BayesLSTM without causal and time-lag characteristics	0.013	0.168	90.8%	0.107

As shown in above tables, the proposed BayesLSTM model demonstrates high predictive accuracy for the deterioration of all three distress types. Its prediction interval coverage reaches 100%, effectively capturing the true values within the intervals. Among them, pothole deterioration exhibits the best performance, with the lowest MAE and MAPE across the three distress types. This can be attributed, on one hand, to the relatively larger number of pothole samples, providing a richer dataset for model training. On the other hand, the shorter deterioration cycle of potholes, which is typically around six months. It reduces issues related to information decay and feature drift compared with longer-term predictions for alligator cracks (1 year) and transverse cracks (1.5 years). So, it can result in lower prediction uncertainty and the smallest NMPIW. Furthermore, unlike the subtle gradual changes in cracks, pothole deterioration is more sensitive to external environmental factors, with formation and progression significantly accelerated by rainfall and water infiltration. This direct causal relationship highlights the effectiveness of incorporating causal and time-lag characteristics in pothole prediction, further enhancing the model's environmental responsiveness and predictive accuracy.

The incorporation of causal characteristics and time-lag characteristics further enhances the overall predictive performance of the model, particularly at inflection points of abrupt deterioration, as illustrated in Figure 17. Without these characteristics, the model primarily relies on historical distress data for trend extrapolation, exhibiting limited sensitivity to sudden changes in deterioration trends. It increases prediction errors near inflection points and reduces overall accuracy. By integrating causal and time-lag characteristics, the model leverages the lag effects of key environmental factors, enabling early detection of potential acceleration signals and improving the prediction of deterioration inflection points. Therefore, both accuracy during abrupt changes and overall predictive performance are enhanced. Compared with the conventional LSTM, the BayesLSTM benefits from the inclusion of Dropout layers, which significantly improves prediction accuracy. Dropout

randomly deactivates neurons during training, reducing co-adaptation, enhancing generalization, and improving robustness to test data. Additionally, it enables the construction of prediction intervals, mitigating the influence of outliers in point predictions and further increasing the stability and reliability of the results.

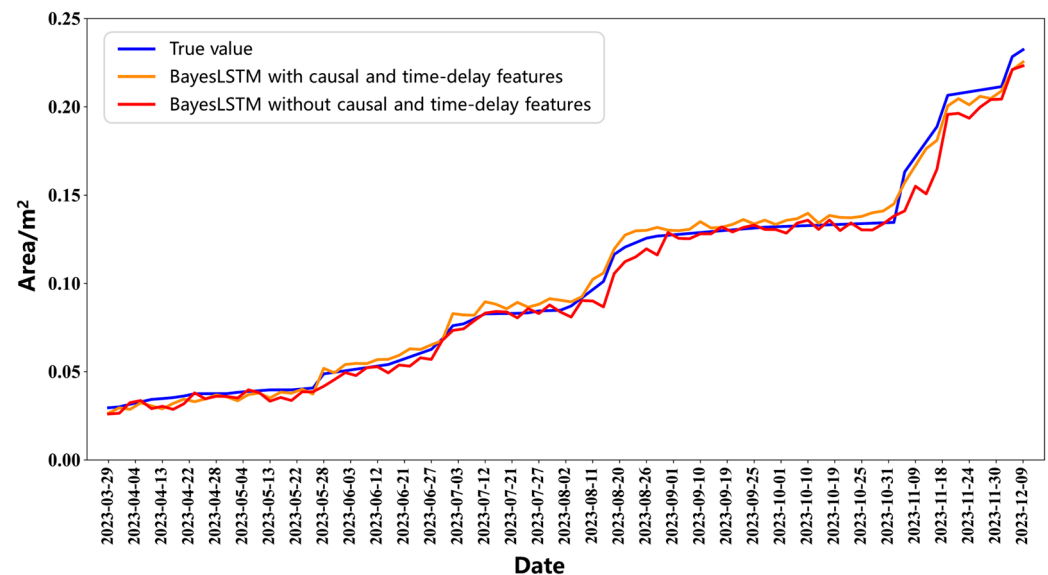


Figure 17. Comparison of prediction results with the introduction of causal lag characteristics.

5. Conclusions

This study focuses on the distress-level deterioration prediction of pavement distresses with causal analysis and uncertainty quantification. Convergent Cross Mapping was first employed to quantify the causal strength and lag days of environmental factors on transverse cracks, alligator cracks, and potholes. Subsequently, Monte Carlo Dropout was introduced to capture model uncertainty, enabling an integrated characterization of distress-level predictions and their interval estimation. Based on these analyses, the main conclusions are as follows:

- (1) A tracking dataset for three distress types was constructed using two years of road inspection data. A three-level matching method was applied to trace the same distress across time and space and to precisely quantify its dimension throughout the deterioration process. The resulting dataset covers 164 locations and contains 9038 records.
- (2) The proposed BayesLSTM model achieved high accuracy in predicting the deterioration of three distress types, with prediction interval coverage reaching 100%, thereby improving the reliability of results. Pothole prediction performed best, benefiting from its shorter deterioration cycle and higher sensitivity to environmental factors. The integration of causal time-lag characteristics further enhanced the model's ability to identify key factors and anticipate inflection points.
- (3) Incorporating causal strength and time-lag characteristics improved the model's capacity to detect critical factors and to forecast deterioration inflection points in advance. Compared with conventional LSTM, BayesLSTM leverages Dropout layers to enhance generalization and construct prediction intervals, reducing the influence of outliers and yielding more stable and reliable forecasts.

These results offer a technical foundation for routine maintenance and maintenance priority assessment, supporting the identification of high-risk areas and their driving mechanisms. Through enabling proactive adjustments to maintenance schedules, limited resources can be reallocated to areas more susceptible to damage. However, the model's adaptability to multi-scenario and multi-scale conditions remains limited. Future research

should explore its applicability across different regions, climates, traffic compositions, and pavement structures. Incorporating additional factors, such as maintenance history or subgrade conditions, could enhance the model's robustness and predictive accuracy. For instance, regional partitioning and locally adaptive parameters could be incorporated to account for variations in climate, structural types, and traffic loads, thereby improving the model's generalizability.

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References

1. Naseri, H.; Aliakbari, A.; Javadian, M.A.; Waygood, E. A Novel Technique for Multi-Objective Sustainable Decisions for Pavement Maintenance and Rehabilitation. *Case Stud. Constr. Mater.* **2024**, *20*, e03037. [\[CrossRef\]](#)
2. Park, B.; Zhang, C.; Cho, S.; Nantung, T.E.; Haddock, J.E. Decision Framework to Determine the Maintenance Strategy Based on Both Structural and Functional Conditions of Asphalt Pavements. *Transp. Res. Rec.* **2025**, *2679*, 774–787. [\[CrossRef\]](#)
3. Ding, T.; Wang, H. Decision Tree Implementation for Pavement Maintenance and Repair Based on Neural Network Model. In Proceedings of the 2024 International Academic Conference on Edge Computing, Parallel and Distributed Computing, Xi'an China, 19–21 April 2024; ACM: New York, NY, USA; pp. 170–174.
4. Huang, L.-L.; Lin, J.-D.; Huang, W.-H.; Kuo, C.-H.; Chiou, Y.-S.; Huang, M.-Y. Developing Pavement Maintenance Strategies and Implementing Management Systems. *Infrastructures* **2024**, *9*, 101. [\[CrossRef\]](#)
5. Ashqar, H.I.; Issa, A.; Masri, S. A Software for Predicting Pavement Condition Index (PCI) Using Machine Learning for Practical Decision-Making with an Exclusion Approach. *SoftwareX* **2025**, *31*, 102304. [\[CrossRef\]](#)
6. Pan, Y.; Liu, G.; Tang, D.; Han, D.; Li, X.; Zhao, Y. A Rutting-Based Optimum Maintenance Decision Strategy of Hot in-Place Recycling in Semi-Rigid Base Asphalt Pavement. *J. Clean. Prod.* **2021**, *297*, 126663. [\[CrossRef\]](#)
7. Han, C.; Ma, T.; Chen, S. Asphalt Pavement Maintenance Plans Intelligent Decision Model Based on Reinforcement Learning Algorithm. *Constr. Build. Mater.* **2021**, *299*, 124278. [\[CrossRef\]](#)
8. Luo, Z. Pavement Performance Modelling with an Auto-Regression Approach. *Int. J. Pavement Eng.* **2013**, *14*, 85–94. [\[CrossRef\]](#)
9. Pan, N.-F.; Ko, C.-H.; Yang, M.-D.; Hsu, K.-C. Pavement Performance Prediction through Fuzzy Regression. *Expert Syst. Appl.* **2011**, *38*, 10010–10017. [\[CrossRef\]](#)
10. Makendran, C.; Murugasan, R.; Velmurugan, S. Performance Prediction Modelling for Flexible Pavement on Low Volume Roads Using Multiple Linear Regression Analysis. *J. Appl. Math.* **2015**, *2015*, 192485. [\[CrossRef\]](#)
11. Bhandari, S.; Luo, X.; Wang, F. Understanding the Effects of Structural Factors and Traffic Loading on Flexible Pavement Performance. *Int. J. Transp. Sci. Technol.* **2023**, *12*, 258–272. [\[CrossRef\]](#)
12. Zhao, J.; Wang, H.; Lu, P. Impact Analysis of Traffic Loading on Pavement Performance Using Support Vector Regression Model. *Int. J. Pavement Eng.* **2022**, *23*, 3716–3728. [\[CrossRef\]](#)
13. Shafiee, M.; Fattahi, M.; Roshani, E.; Popov, P. Enhanced Prediction of Urban Road Pavement Performance under Climate Change with Machine Learning. *J. Civ. Eng. Constr.* **2024**, *13*, 159–169. [\[CrossRef\]](#)

14. Gudipudi, P.P.; Underwood, B.S.; Zalgout, A. Impact of Climate Change on Pavement Structural Performance in the United States. *Transp. Res. Part D Transp. Environ.* **2017**, *57*, 172–184. [\[CrossRef\]](#)
15. Zeiada, W.; Dabous, S.A.; Hamad, K.; Al-Ruzouq, R.; Khalil, M.A. Machine Learning for Pavement Performance Modelling in Warm Climate Regions. *Arab. J. Sci. Eng.* **2020**, *45*, 4091–4109. [\[CrossRef\]](#)
16. Gong, H.; Sun, Y.; Hu, W.; Polaczyk, P.A.; Huang, B. Investigating Impacts of Asphalt Mixture Properties on Pavement Performance Using LTPP Data through Random Forests. *Constr. Build. Mater.* **2019**, *204*, 203–212. [\[CrossRef\]](#)
17. Hou, H.; Wang, T.; Wu, S.; Xue, Y.; Tan, R.; Chen, J.; Zhou, M. Investigation on the Pavement Performance of Asphalt Mixture Based on Predicted Dynamic Modulus. *Constr. Build. Mater.* **2016**, *106*, 11–17. [\[CrossRef\]](#)
18. Ziari, H.; Maghrebi, M.; Ayoubinejad, J.; Waller, S.T. Prediction of Pavement Performance: Application of Support Vector Regression with Different Kernels. *Transp. Res. Rec.* **2016**, 2589, 135–145. [\[CrossRef\]](#)
19. Wang, X.; Zhao, J.; Li, Q.; Fang, N.; Wang, P.; Ding, L.; Li, S. A Hybrid Model for Prediction in Asphalt Pavement Performance Based on Support Vector Machine and Grey Relation Analysis. *J. Adv. Transp.* **2020**, *2020*, 7534970. [\[CrossRef\]](#)
20. Tabatabaee, N.; Ziyadi, M.; Shafahi, Y. Two-Stage Support Vector Classifier and Recurrent Neural Network Predictor for Pavement Performance Modeling. *J. Infrastruct. Syst.* **2012**, *19*, 266–274. [\[CrossRef\]](#)
21. Yu, T.; Pei, L.-I.; Li, W.; Sun, Z.; Huan, J. Pavement Surface Condition Index Prediction Based on Random Forest Algorithm. *J. Highw. Transp. Res. Dev.* **2021**, *15*, 1–11. [\[CrossRef\]](#)
22. Gong, H.; Sun, Y.; Shu, X.; Huang, B. Use of Random Forests Regression for Predicting IRI of Asphalt Pavements. *Constr. Build. Mater.* **2018**, *189*, 890–897. [\[CrossRef\]](#)
23. Mers, M.; Yang, Z.; Hsieh, Y.-A.; Tsai, Y.J. Recurrent Neural Networks for Pavement Performance Forecasting: Review and Model Performance Comparison. *Transp. Res. Rec.* **2023**, 2677, 610–624. [\[CrossRef\]](#)
24. Wu, Y.; Zhang, Q.; Wang, Y.; Zhu, X. Advanced Hybrid CNN-GRU Model for IRI Prediction in Flexible Asphalt Pavements. *J. Transp. Eng. Part B Pavements* **2025**, *151*, 04025003. [\[CrossRef\]](#)
25. Li, W.; Chen, X.; Yang, X.; Xu, D. Highway Pavement Temperature Short-Term Prediction Model Based on Multi-Layer GRU. In Proceedings of the 2023 7th International Conference on Electronic Information Technology and Computer Engineering, Xiamen, China, 20–22 October 2023; pp. 516–522, ISBN 979-8-4007-0830-5.
26. Adlinge, S.S.; Gupta, A.K. Pavement Deterioration and Its Causes. *IOSR J. Mech. Civ. Eng.* **2013**, *2*, 437–450.
27. Cammarata, J.E.; Hariharan, N.; Allen, D.H.; Little, D.N. A Study of Moisture-Induced Cracking during a Short-Term Rain Event in a Pre-Cracked Asphalt Concrete Pavement with an Expansive Base Layer. *Int. J. Pavement Eng.* **2020**, *21*, 1180–1190. [\[CrossRef\]](#)
28. Liu, H.; Li, Y.; Liu, C.; Shen, G.; Xiang, H. Pavement Distress Initiation Prediction by Time-Lag Analysis and Logistic Regression. *Appl. Sci.* **2022**, *12*, 11855. [\[CrossRef\]](#)
29. Li, Y.; Liu, C.; Du, Y.; Jiang, S. A Novel Evaluation Method for Pavement Distress Based on Impact of Ride Comfort. *Int. J. Pavement Eng.* **2020**, *23*, 638–650. [\[CrossRef\]](#)
30. Roberts, C.A.; Attoh-Okine, N.O. A Comparative Analysis of Two Artificial Neural Networks Using Pavement Performance Prediction. *Comput. Aided Civ. Eng.* **1998**, *13*, 339–348. [\[CrossRef\]](#)
31. Li, Y.; Liu, C.; Gao, Q.; Wu, D.; Li, F.; Du, Y. ConTrack Distress Dataset: A Continuous Observation for Pavement Deterioration Spatio-Temporal Analysis. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 25004–25017. [\[CrossRef\]](#)
32. Li, Y.; Liu, C.; Weng, Z.; Wu, D.; Du, Y. Aggregate-Level 3D Analysis of Asphalt Pavement Deterioration Using Laser Scanning and Vision Transformer. *Autom. Constr.* **2025**, *178*, 106380. [\[CrossRef\]](#)
33. Dong, Q.; Chen, X.; Dong, S.; Ni, F. Data Analysis in Pavement Engineering: An Overview. *IEEE Trans. Intell. Transp. Syst.* **2021**, *23*, 22020–22039. [\[CrossRef\]](#)
34. Lv, S.; Xia, C.; Liu, H.; You, L.; Qu, F.; Zhong, W.; Yang, Y.; Washko, S. Strength and Fatigue Performance for Cement-Treated Aggregate Base Materials. *Int. J. Pavement Eng.* **2021**, *22*, 690–699. [\[CrossRef\]](#)
35. Cheng, H.; Sun, L.; Wang, Y.; Chen, X. Effects of Actual Loading Waveforms on the Fatigue Behaviours of Asphalt Mixtures. *Int. J. Fatigue* **2021**, *151*, 106386. [\[CrossRef\]](#)
36. Xie, N.; Li, H.; Abdelhady, A.; Harvey, J. Laboratorial Investigation on Optical and Thermal Properties of Cool Pavement Nano-Coatings for Urban Heat Island Mitigation. *Build. Environ.* **2019**, *147*, 231–240. [\[CrossRef\]](#)
37. Xie, N.; Li, H.; Zhang, H.; Zhang, X.; Jia, M. Effects of Accelerated Weathering on the Optical Characteristics of Reflective Coatings for Cool Pavement. *Sol. Energy Mater. Sol. Cells* **2020**, *215*, 110698. [\[CrossRef\]](#)
38. Sarlin, P.-E.; DeTone, D.; Malisiewicz, T.; Rabinovich, A. Superglue: Learning Feature Matching with Graph Neural Networks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Seattle, WA, USA, 13–19 June 2020; pp. 4938–4947.
39. *JTG H20-2018*; Highway Performance Assessment Standard. Ministry of Transport of the People’s Republic of China: Beijing, China, 2019.
40. Yang, H.; Cao, J.; Wan, J.; Gao, Q.; Liu, C.; Fischer, M.; Du, Y.; Li, Y.; Jain, P. A Large-Scale Image Repository for Automated Pavement Distress Analysis and Degradation Trend Prediction. *Sci. Data* **2025**, *12*, 1426. [\[CrossRef\]](#)

41. Sugihara, G.; May, R.; Ye, H.; Hsieh, C.; Deyle, E.; Fogarty, M.; Munch, S. Detecting Causality in Complex Ecosystems. *Science* **2012**, *338*, 496–500. [[CrossRef](#)]
42. Deyle, E.R.; Maher, M.C.; Hernandez, R.D.; Basu, S.; Sugihara, G. Global Environmental Drivers of Influenza. *Proc. Natl. Acad. Sci. USA* **2016**, *113*, 13081–13086. [[CrossRef](#)]
43. Jordan, M.I.; Ghahramani, Z.; Jaakkola, T.S.; Saul, L.K. An Introduction to Variational Methods for Graphical Models. *Mach. Learn.* **1999**, *37*, 183–233. [[CrossRef](#)]
44. Gal, Y.; Ghahramani, Z. A Theoretically Grounded Application of Dropout in Recurrent Neural Networks. *Adv. Neural Inf. Process. Syst.* **2016**, *29*, 1027–1035.
45. Srivastava, N.; Mansimov, E.; Salakhudinov, R. Unsupervised Learning of Video Representations Using LSTMs. In Proceedings of the International Conference on Machine Learning, PMLR, Lille, France, 6–11 July 2015; pp. 843–852.
46. Berenji Ardestani, S. Time Series Anomaly Detection and Uncertainty Estimation Using LSTM Autoencoders. Master's Thesis, KTH School of Electrical Engineering and Computer Science, Stockholm, Sweden, 2020.
47. Zhu, L.; Laptev, N. Deep and confident prediction for time series at uber. In Proceedings of the 2017 IEEE International Conference on Data Mining Workshops (ICDMW), New Orleans, LA, USA, 18–21 November 2017; pp. 103–110.
48. Khosravi, A.; Nahavandi, S.; Creighton, D.; Atiya, A.F. Lower Upper Bound Estimation Method for Construction of Neural Network-Based Prediction Intervals. *IEEE Trans. Neural Netw.* **2010**, *22*, 337–346. [[CrossRef](#)] [[PubMed](#)]

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