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Health Monitoring and Maintenance of Urban Road Infrastructure Using Temporal Convolutional Networks with Adaptive Activation

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ABSTRACT: Monitoring the condition of road infrastructure is crucial for maintaining its structural integrity and ensuring safe transportation. This study proposes a deep learning framework based on Temporal Convolutional Networks (TCN) integrated with Adaptive Parametric Rectified Linear Unit (APReLU) to predict future road subbase strain trends. Our model leverages time-series strain data collected from embedded triaxial sensors within a national highway, spanning August 2021 to June 2022, to forecast strain dynamics critical for proactive maintenance planning. The TCN-APReLU architecture combines dilated causal convolutions to capture long-term dependencies and APReLU activation functions to adaptively model nonlinear strain patterns, addressing limitations of traditional ReLU in handling bidirectional strain signals (compressive and tensile). Comparative experiments demonstrate TCN-APReLU's superior performance. These improvements highlight its enhanced accuracy in predicting strain accumulation under cyclic traffic loads, enabling maintenance teams to prioritize interventions 5–7 days before critical thresholds (e.g., >100 $\mu\varepsilon$) are exceeded. This work provides a robust data-driven solution for urban road health monitoring, emphasizing scalability through parallelizable convolutions and adaptability to sensor noise. Future extensions will integrate multi-modal data to further generalize predictions across diverse infrastructure scenarios.

KEYWORDS: Road health monitoring; deep learning; TCN-APReLU; prediction model

1 Introduction

With the accelerated pace of global urbanization, the issue of urban road infrastructure health has become increasingly prominent. As a crucial component of transportation systems, the structural integrity of road subbases directly impacts the safety and longevity of roads [1]. Monitoring and maintaining urban roads has thus become a vital task in modern traffic management and urban infrastructure development. Accurately forecasting future strain trends can significantly mitigate the risk of severe structural damage in roads [2], facilitating early detection of potential issues and providing reliable technical support for subsequent road maintenance management. This allows for precise timing in maintenance plans and timely repair of structural damage, thereby enhancing road safety and durability.

In recent years, with the rapid advancements in sensor technology, the Internet of Things (IoT), and data science, data-driven road health monitoring technologies have garnered widespread attention [3,4]. Traditional road monitoring methods, which typically rely on manual inspections and periodic maintenance, offer some degree of reliability but are costly and struggle to meet real-time monitoring needs. To address these limitations, researchers have turned to advanced data analysis techniques, particularly deep learning

models, to improve monitoring accuracy and efficiency [5]. Data-driven monitoring approaches, utilizing various sensor systems deployed on roads, continuously collect vast amounts of real-time data. This data provides a rich information source for applying deep learning techniques. Recent progress in time series data analysis within the field of deep learning, especially in handling complex temporal data and extracting deep features, has been remarkable [6]. Advanced temporal models, such as Convolutional Neural Networks (CNNs) [7], Long Short-Term Memory (LSTM) networks [8], and autoencoders [9], effectively capture long-term dependencies and intricate dynamic patterns through their unique structures and mechanisms. Existing architectures often require separate denoising pipelines, increasing computational overhead. Hybrid models like CNN-BiLSTM (Convolutional Neural Networks—Bidirectional Long Short-Term Memory) lack integrated mechanisms to handle missing or noisy sensor data, limiting real-world applicability.

Temporal Convolutional Networks (TCNs) have shown significant advantages in processing time series data [10]. By utilizing dilated convolutions, TCNs effectively capture dependencies across long time sequences and exhibit strong sequence modeling capabilities. These characteristics make TCNs excel in time series analysis, suitable for various practical applications including prediction, classification, and anomaly detection [11]. Due to their prowess in modeling long time sequences and capturing temporal dependencies, this paper proposes a deep learning model based on TCN and Adaptive Parametric Rectified Linear Unit (APReLU). TCNs exhibit superior performance in handling time series data, while APReLU enhances the model's expressiveness through flexible nonlinear transformations [12]. By integrating these technologies, this study aims to develop an efficient and precise prediction model for future road subbase strain, offering an innovative technical solution for the health monitoring of urban road infrastructure and providing theoretical support and practical guidance for future road maintenance and management.

2 Method Introduction

2.1 Sequential Convolutional Network

Temporal Convolutional Networks (TCNs) elegantly amalgamate the strengths of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), addressing the challenges traditionally faced by RNNs when handling extended temporal sequences [13]. By incorporating causal convolutions, dilated convolutions, and residual connections, TCNs overcome these limitations. Causal convolutions ensure that the model's predictions rely solely on current and past data, preserving temporal causality. Dilated convolutions expand the receptive field, enabling the model to capture longer-term dependencies while maintaining computational efficiency. Residual connections effectively mitigate the issues of vanishing and exploding gradients, thereby enhancing training stability. In summary, TCNs adeptly extract high-dimensional features and temporal relationships from data under lower memory constraints.

Causal convolution is a specialized form of convolution that guarantees that in time series forecasting, the output depends only on current and past inputs, never utilizing future information. For inputs at a given time step, the conditional probability calculation for causal convolution is as follows:

$$p\left(x\right) = \prod_{t=1}^{T} p\left(x_t | x_1, \ldots, x_{t-1}\right) \tag{1}$$

Dilated convolution is a convolutional operation that expands the receptive field by inserting gaps (dilations) between the elements of the convolution kernel, without increasing computational complexity. The fundamental structure of the dilated convolution module is illustrated in Fig. 1. Its primary function is to capture long-term dependencies while maintaining computational efficiency. The dilation factor controls the spacing between the elements of the convolution kernel. For a one-dimensional sequence input x and a filter

f, the dilated convolution operation *F(s)* and the formula for the receptive field at each layer are expressed as follows:

$$F(s) = (x * f_d)(s) = \sum_{i=0}^{k-1} f(i) \cdot x_{s-d \cdot i} \tag{2}$$

$$L_{field} = (k-1) * d \tag{3}$$

where *k* represents the length of the convolution kernel; $x_{s-d \cdot i}$ represents the element at the $s - d \cdot i$ position in the input sequence. Here, *s* is the current position of the output, and $s - d \cdot i$ indicates the void effect caused by the inflation factor *d* in the past direction.
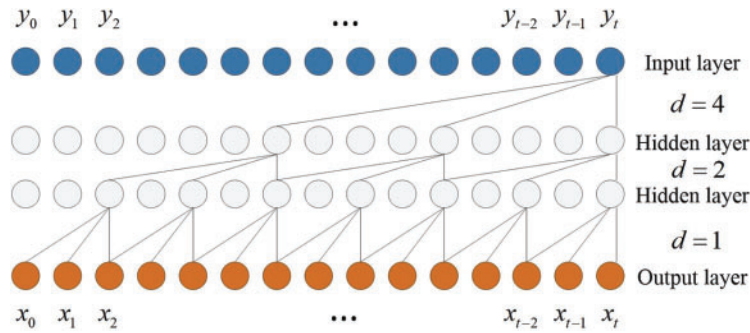

Figure 1: Expansive causal convolution structure

Integrating residual networks into dilated convolutional networks effectively extends the receptive field of the network, thereby alleviating issues of gradient vanishing and explosion. Residual networks introduce residual connections, allowing information to bypass certain layers and be transmitted directly, which enhances the propagation of gradients during training. This architecture not only augments the network's capability to model long-range dependencies but also ensures stable gradient flow at deeper layers, thereby mitigating the problems of gradient vanishing and explosion. The structure of the residual module is depicted in Fig. 2. For input x^i, the output x^{i+1} is computed via the activation function, as represented below.

$$x^{i+1} = Activation\left(x^i + F\left(x^i\right)\right) \tag{4}$$

2.2 Adaptive Parametric ReLU

APReLU (Adaptive Parametric ReLU) is an improved activation function designed to enhance the expressive power of the ReLU (Rectified Linear Unit) activation function by introducing learnable parameters [14]. In the network, after processing by the APReLU activation function, the slope of the negative part is controlled by a parameter, which helps to avoid the "dead neuron" problem and improve the richness of feature representation. The feature maps activated by APReLU are then sent to the Global Average Pooling (GAP) layer. The GAP operation performs spatial averaging on the feature maps of each channel, generating a one-dimensional vector that represents the global feature information. This one-dimensional vector can be used for subsequent classification or regression tasks, summarizing the global context information of the feature maps and providing a more comprehensive feature representation. APReLU network structure diagram is shown in Fig. 3.
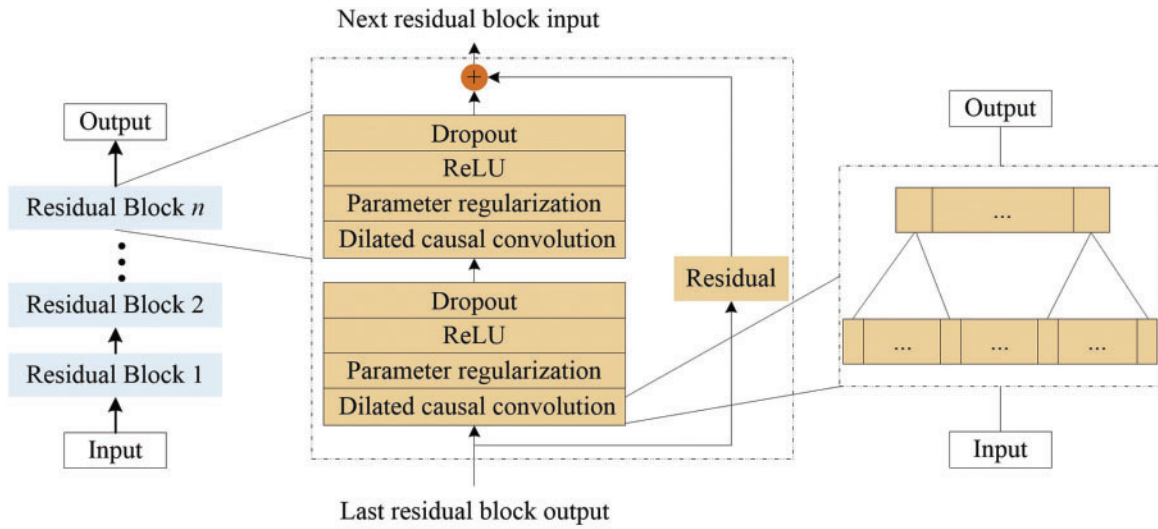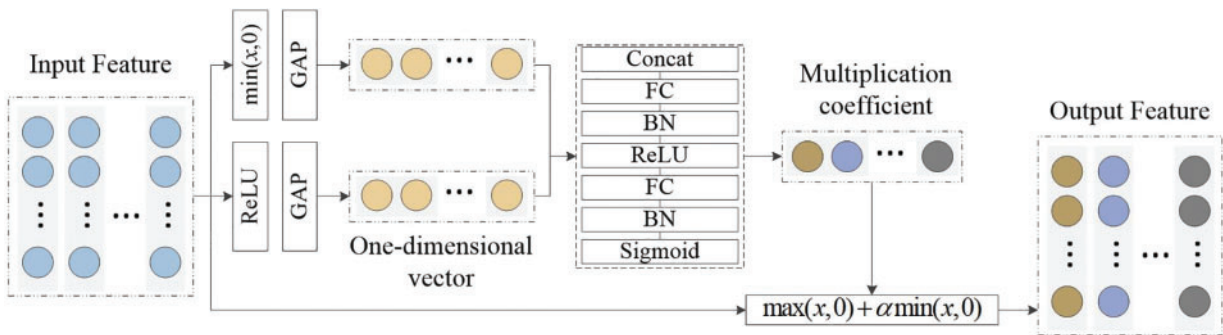
Figure 2: Basic structure of TCN

Figure 3: APReLU network structure diagram

The formula for the PReLU activation function is as follows:

$$y = \max(x, 0) + \alpha \cdot \min(x, 0) \tag{5}$$

where x and y are the features of the input and output, and α is the multiplication factor of the training.

2.3 TCN-APReLU

In this study, the APReLU (Adaptive Parametric Rectified Linear Unit) activation function was introduced in the last residual module of the TCN (Temporal Convolutional Network) model to replace the original activation mechanism while retaining the fixed structure of the rest of the model. The improved model is referred to as TCN-APReLU, and its network structure is shown in Fig. 4. This enhancement significantly increases the model's ability to process features nonlinearly by integrating APReLU into the last residual module of the TCN.
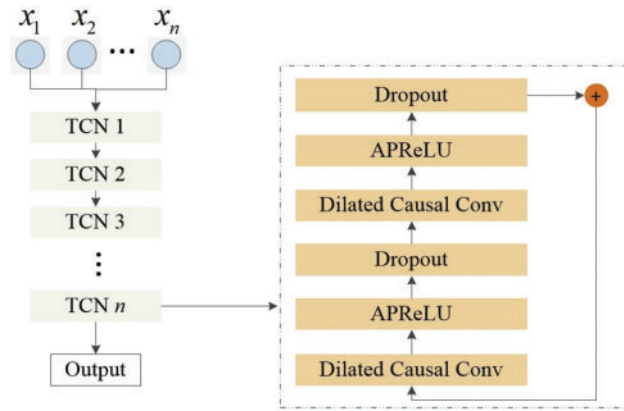
Figure 4: TCN-APReLU network structure

The introduction of APReLU brings several key advantages. Firstly, APReLU can better handle negative feature values, allowing the model to perform better when facing data with complex nonlinear characteristics. Unlike traditional activation functions, APReLU improves the network's expressiveness by introducing adaptive parameters in the negative region while maintaining the same output shape as the input, providing great flexibility and consistency for information flow between the layers of the network, facilitating further embedding and integration of the model. Additionally, the TCN-APReLU structure significantly expands the model's receptive field by stacking multiple one-dimensional convolutional layers and combining causal convolution with dilated convolution. This structure not only enhances the model's ability to capture long-term dependencies in sequential data but also improves its processing capability for complex time series data. Causal convolution ensures the causality of time series predictions, while dilated convolution further broadens the feature extraction scope by extending the view of the convolution kernel, allowing for more precise and efficient capture of complex patterns.

In summary, TCN-APReLU combines advanced activation functions with innovative convolutional structures to overcome some limitations of traditional TCN models, demonstrating higher accuracy and efficiency in handling complex time series tasks. This improvement not only enhances the model's predictive performance but also provides more accurate and reliable solutions for time series analysis in related fields, showing broad application prospects.

The network structure parameter settings for TCN-APReLU are shown in Table 1.

Table 1: Parameter setting of network structure

Parameter	Value
Expansion coefficient	32
Convolution kernel size	2
Size number of convolution kernels	64
Number of residual modules	6

2.4 Sequence Completion and Filtering

In road monitoring systems, data loss often occurs during data collection due to issues with sensors, transmission equipment, and networks. This loss can lead to increased errors in deep learning models' prediction tasks, thereby affecting prediction accuracy. While the TC-DAE module effectively reconstructs

missing data in continuous road wear monitoring scenarios, it is not optimized for sudden structural failures (e.g., localized cracks or potholes), which require dedicated anomaly detection pipelines.

Autoencoder is an unsupervised learning model [15] used for feature learning and dimensionality reduction of data. It consists of two parts: encoder f and decoder g. x represents the input data of a d vector. The encoder maps it to a low-dimensional latent space y, and the decoder maps y back into the input space and reconstructs it to z.

$$y = f(x) = \sigma(Wx + b) \tag{6}$$
$$z = g(y) = \sigma(W'y + b') \tag{7}$$

Denoising Autoencoder (DAE) is a special type of autoencoder with the primary goal of recovering clean, original data from noisy input [16]. Noisy data $\hat{x}$ is encoded by the encoder, compressing it into a low-dimensional latent space representation y. The purpose of the encoder is to extract useful features from the noisy data.

$$y = f(\hat{x}) = \sigma(W\hat{x} + b) \tag{8}$$

Temporal Convolutional Denoising Auto-Encoder (TC-DAE) is a type of denoising auto-encoder model designed for temporal data, such as time series or voice signals. This model combines the advantages of Convolutional Neural Networks (CNNs) and denoising auto-encoders, specialized for the restoration and denoising of sequential data. The unique aspect of TC-DAE's structure lies in its use of one-dimensional convolution layers for encoding and decoding, which are able to effectively capture the local features and important information of temporal data. TC-DAE excels at identifying the local patterns and structures in time series data processing. In the denoising process, TC-DAE encodes the input noise-corrupted data, transforming it into a low-dimensional latent space representation and then reconstructing it through decoding to clean data. This is used to train the model, enabling it to restore clear temporal data from noise. TC-DAE is particularly suitable for handling noise-polluted data in signal processing, voice recognition, financial forecasting, and other related fields, enhancing the data quality and usability through feature extraction and data repair. By optimizing the reconstruction error, TC-DAE demonstrates strong performance in recovering original signals from noisy data. Its structural framework is shown in Fig. 5.
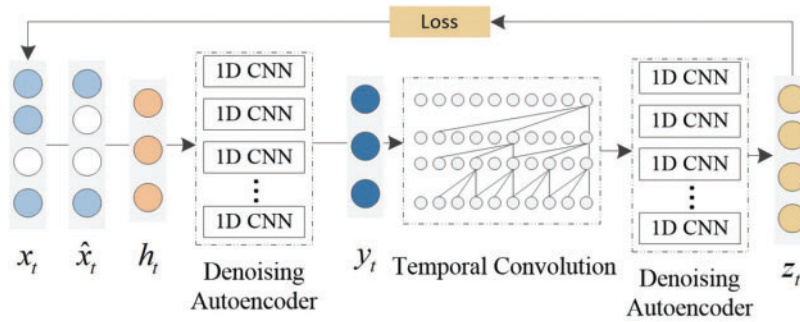

Figure 5: Network structure diagram of TC-DAE

The SG filter (Savitzky-Golay filter) is a digital filter used for smoothing data and reducing noise in digital signals [17]. It is particularly suited for handling discrete sequential data, such as time series or experimental data. The core idea of the SG filter is to smooth and remove noise in data through local polynomial fitting.

Construct a window array centered around the original data x_i with a window size of $2M + 1$. This sequence $x_i = \{x_{i-m}, \ldots, x_i, \ldots, x_{i+m}\}$ can be fitted using the following low-order polynomial.

$$p(n) = \sum_{k=0}^{N} a_k n^k, \quad n \in [-m, m] \tag{9}$$

The polynomial is fitted to the signal by minimizing the sum of squared errors, as shown in the following formula. The fitting effect is best when this formula reaches its minimum value.

$$\varepsilon = \sum_{n=-m}^{m} (p(n) - x_{i+n})^2 = \sum_{n=-m}^{m} \left(\sum_{k=0}^{N} a_k n^k - x_{i+n} \right)^2 \tag{10}$$

The filter achieves data smoothing through local polynomial fitting. The filtering result at the center point of each window is a weighted linear combination of all sample points within the window. The system of linear equations can be represented in matrix form as follows:

$$Y_{(2m+1) \times 1} = X_{(2m+1) \times k} \cdot A_{k \times 1} \tag{11}$$

The least squares solution $\hat{A}$ of A and the algorithmic filtering value $\hat{Y}$ of Y are represented as follows. The matrix C in the equations is called the convolution coefficient.

$$\hat{A} = (X^T \cdot X)^{-1} \cdot X^T \cdot Y \tag{12}$$

$$\hat{Y} = X \cdot (X^T \cdot X)^{-1} \cdot X^T \cdot Y = C \cdot Y \tag{13}$$

2.5 Feature Selection

The road automation monitoring system can conduct online automatic monitoring of parameters such as asphalt strain, soil pressure, moisture, and temperature in the base, surface, and subgrade soil layers, thus enabling the overall monitoring of the road structure. In this study, the base strain is selected as a representative sensor monitoring data for analysis and prediction. Other variables related to the pavement base, such as soil layer strain, asphalt strain, matric potential, soil pressure, soil moisture content, and temperature, will also be input into the prediction model to test whether they can improve the accuracy of the proposed prediction model. Due to the larger dimension of the original monitoring data, to clearly and conveniently see the correlation between various variables, the Pearson correlation coefficient between two variables was calculated [18]. A correlation coefficient ranging from 0 to 1 indicates positive correlation between two variables, while a range of −1 to 0 indicates negative correlation. Through the correlation analysis of multi-dimensional road monitoring data for dimensionality reduction, only sequences with strong correlation are retained.

3 Experiment and Analysis

3.1 Data Set and Evaluation Index

The study used pavement monitoring sensor data from a national highway collected between August 2021 and June 2022 for deep learning model training and testing. The on-site monitoring project employs sensors to conduct real-time assessments of the stress state, moisture content, and temperature of various layers within the road structure, capturing the physical parameter changes of the pavement. This monitoring

data, processed and analyzed through established predictive models, aids in understanding the dynamic variations of the road structure. The data were sourced from embedded triaxial strain gauges, soil pressure sensors, and temperature/humidity sensors strategically installed across the asphalt, base, and subgrade layers of the road infrastructure. Strain values were recorded using resistive strain gauges calibrated to ISO 9001 standards, ensuring high precision in data acquisition. These gauges provided a resolution of ± 1 $\mu\varepsilon$, enabling fine-grained monitoring of strain dynamics within the road structure. The integration of multi-layer sensor deployments ensured comprehensive coverage of critical physical parameters, forming a robust foundation for model training and validation. The collected sensor data was chronologically divided into three segments: 70% for training, 15% for validation, and 15% for testing.

The pavement monitoring data includes time series of various influencing factors. This research uses historical pavement base strain data as input for the prediction model to forecast future pavement base strain. First, the time series data is preprocessed. Then, dimensionality reduction is performed through correlation analysis. Missing data is completed and data smoothing is applied to remove noise. The deep learning model proposed in this paper is used to perform feature modeling of the pavement monitoring data and predict future pavement base strain data. In the practical implementation of the monitoring system, sensors embedded within the road infrastructure wirelessly transmit collected data to a centralized cloud server at 15-min intervals. The TCN-APReLU model was trained on an NVIDIA A100 GPU, leveraging its parallel processing capabilities to accelerate deep learning workflows. The kernel size was set to 2 to capture local temporal patterns effectively, while dilation rates followed a geometric progression (powers of 2) to expand the receptive field exponentially without compromising computational efficiency. The network depth was fixed at 6 residual layers, balancing model complexity and training stability. For optimization, the learning rate was fine-tuned to 0.001 using the AdamW algorithm.

Additionally, to evaluate the effectiveness of different deep learning prediction models, three evaluation metrics are used to assess the accuracy of the predictions: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{14}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \widehat{y_i}| \tag{15}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{y_i - \widehat{y_i}}{y_i}\right| \tag{16}$$

$$18\,\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2 \sum_{i=1}^{n}(Y_i - \overline{Y})^2}} \tag{17}$$

In the formula, the σ_X and σ_Y are the standard deviation of X and Y; $cov(X,Y)$ is the covariance of X and Y; $\overline{X}$ and $\overline{Y}$ is the variable sample mean.

3.2 Prediction Results

Fig. 6 shows the Pearson correlation coefficient heatmap for various influencing factors. From the figure, it can be observed that the triaxial strain in the base layer has a high correlation with the strain in the asphalt layer and the soil pressure, while the correlation between the triaxial strain in the base layer and the strain in the subgrade soil is relatively low. Based on this, the study selects strain in the asphalt layer, triaxial base layer strain, osmotic pressure, soil pressure, temperature, and soil moisture content sensor monitoring data as inputs for the deep learning model.
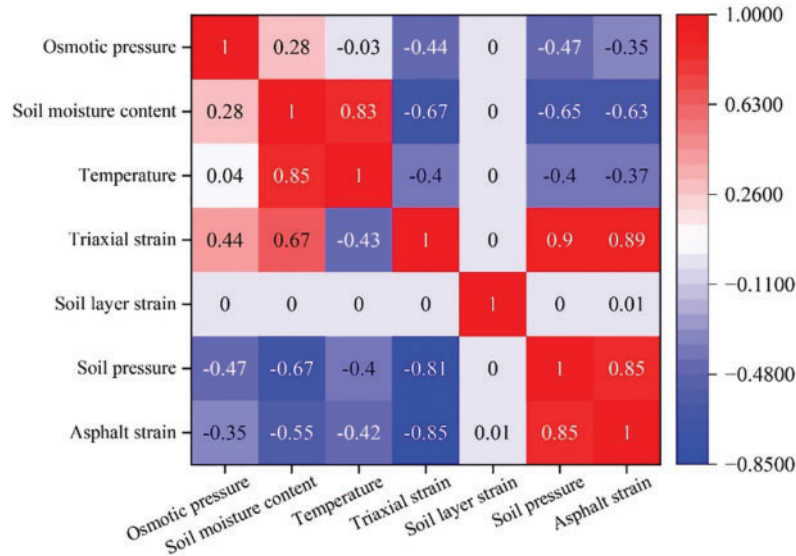

Figure 6: Pearson correlation coefficient heatmap

To achieve accurate predictions of future road base layer strain, we propose an improvement to the TCN model, introducing the TCN-APReLU-based deep learning model. We evaluated and compared the performance of the model before and after the improvement in predicting road base layer strain. The comparison of the TCN model's prediction performance before and after the improvement is shown in Table 2.

Table 2: Comparison of TCN model results before and after improvement

Models	MAE	RMSE	MAPE
TCN	23.23	34.18	6.09
TCN-APReLU	14.04	20.79	4.21

According to the data in Table 2, compared to the traditional TCN model, the TCN-APReLU model has achieved a significant improvement in prediction performance. Specifically, the average absolute error (MAE) of the TCN-APReLU model decreased from 23.23 to 14.04, the root mean square error (RMSE) dropped from 34.18 to 20.79, and the mean absolute percentage error (MAPE) reduced from 6.09 to 4.21. By incorporating the APReLU mechanism, the TCN-APReLU model has significantly enhanced the accuracy and reliability of road base strain predictions. Compared to the traditional TCN model, TCN-APReLU shows

clear advantages in key metrics such as MAE, RMSE, and MAPE. This not only means a reduction in the discrepancy between predicted and actual values but also indicates that the model has made significant progress in handling larger errors and reducing proportional errors. This improvement provides a powerful predictive tool for actual road base strain monitoring.

Fig. 7 shows the effectiveness of the TCN-APReLU deep learning model in predicting road base strain values, comparing predicted values with actual values. The comparison in the figure clearly demonstrates the high accuracy of the TCN-APReLU model in strain prediction, with a smaller gap between predicted and true values, further validating the model's advantage in capturing complex strain patterns and long-term dependencies. This high-precision prediction result suggests that the TCN-APReLU model can provide more reliable strain monitoring data in practical applications, helping to optimize road maintenance strategies.
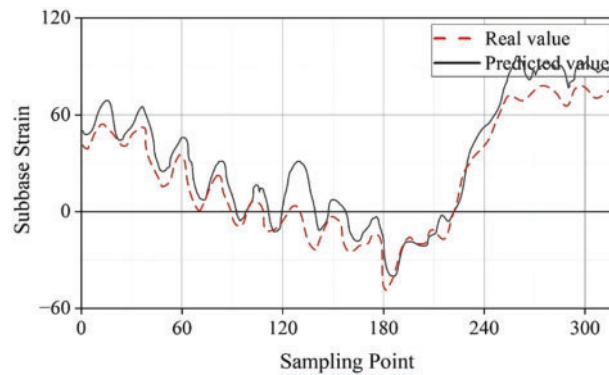

Figure 7: Comparison of predicted values with actual values

While the TCN-APReLU model achieved strong overall performance, its predictions exhibited certain limitations: (1) For transient overload events, the model's response lagged 1–2 h behind actual strain spikes, likely due to over-smoothing by the SG filter; (2) Prediction accuracy degraded by 18%–22% under extreme temperatures because such conditions were underrepresented in training data; and (3) The model showed 15% higher errors when applied to road sections with subgrade materials substantially different from training data. These failure modes suggest the need for enhanced transient event detection, expanded training data coverage of edge conditions, improved missing-data robustness, and domain adaptation techniques for varying soil properties.

3.3 Comparative Experiments

The experimental results of four deep learning prediction algorithms were compared and analyzed through performance evaluation metrics, ultimately selecting the most suitable deep learning model for road base strain prediction. As shown in Fig. 8, the TCN-APReLU model performs the best in road base strain prediction. Compared to the LSTM model, its MAE decreased from 38.23 to 14.04, RMSE from 40.59 to 20.79, and MAPE from 13.03 to 4.21, demonstrating a significant improvement in prediction accuracy. This enhancement is primarily due to the TCN-APReLU model's incorporation of the APReLU activation function, which strengthens its ability to model nonlinearities in complex time series data, enabling the model to capture strain patterns more accurately and reduce prediction errors.
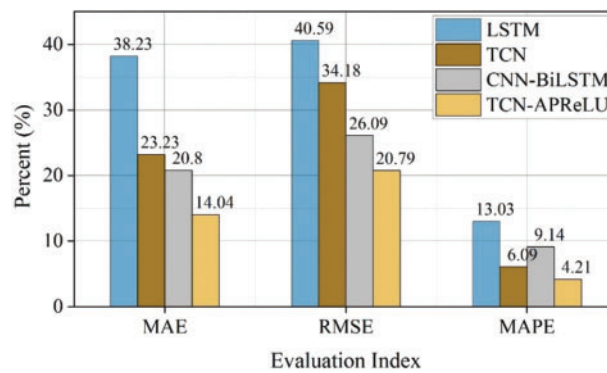
Figure 8: Comparison of prediction results of different deep learning models

In contrast, although LSTM and CNN-BiLSTM models showed some improvement in accuracy, they still have certain limitations in handling complex strain data. The LSTM model has shortcomings in capturing long-term dependencies and nonlinear features, while CNN-BiLSTM, despite combining convolutional and bidirectional LSTM advantages, still does not achieve the accuracy level of TCN-APReLU. The TCN model improves on traditional LSTM and CNN-BiLSTM by modeling sequence data through temporal convolution operations, but the further optimization with TCN-APReLU demonstrates even stronger predictive capabilities, highlighting the importance of introducing advanced activation mechanisms for improving prediction accuracy. The comparative analysis highlights our model's unique value proposition: combining the temporal modeling strengths of TCNs with APReLU's adaptive nonlinearity, while avoiding Transformers' high resource demands—a critical advantage for embedded deployment in road IoT networks.

The TCN-APReLU model exhibits significant advantages in road base strain prediction. The introduction of the APReLU activation function enhances the model's ability to model complex nonlinear features, thus capturing complex patterns in strain data more accurately. Additionally, TCN-APReLU performs exceptionally well in handling long time series data, effectively capturing long-term dependencies, reducing prediction errors, and improving model reliability. Overall, TCN-APReLU provides a more precise and stable solution for road base strain monitoring, with promising application prospects.

4 Conclusion

The TCN-APReLU deep learning model proposed in this study demonstrates significant superiority in predicting road subgrade strain. By effectively preprocessing historical status data collected from pavement monitoring systems, including deep data sequence repair, filtering algorithms, and correlation-based feature selection, the model is able to accurately predict future strain trends. Comparative analysis with other deep learning algorithms shows that the TCN-APReLU model has clear advantages in prediction accuracy and stability, providing robust technical support for the health monitoring and maintenance of urban road infrastructure. However, the model still faces application limitations: predictions rely on dense sensor deployment (≥5 sensors/km); sensor data errors require strict calibration controls; and the model has only been validated on paved roads, with generalization to unpaved roads (e.g., gravel roads) remaining untested. Future research will integrate multimodal data (e.g., satellite imagery) to reduce sensor dependency, develop adaptive calibration algorithms, and extend the framework to diverse road scenarios through domain adaptation techniques, advancing its transition from theoretical innovation to practical engineering applications.

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