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Article

A framework based on deep learning and the intelligent sensors for pavement assessment condition

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Abstract: Long-term pavement performance is a key topic in highway engineering. By diving deep into research on pavement systems, we can bring together past, fragmented knowledge and experiences into a solid, comprehensive engineering theory. This essentially helps guide practical work like pavement design, construction, maintenance, and management. In this research, we look at using a mentoring system for automatic monitoring of pavement performance. By placing various sensors in different positions like the road surface, base, and slopes, a sensor network powered by Internet of Things technology is created. This setup allows for accurate and ongoing observation of factors like weather, physical condition, mechanical responses, and structural changes. Given the large volume of data and the need for real-time analysis, a data from sensors measuring temperature, humidity, pressure, asphalt strain, and displacement are used to train a deep learning model based on a Convolutional Neural Network (CNN) algorithm. This model helps predict multi-point displacement in the pavement, which allows us to detect issues like pavement damage. Impressively, the CNN model achieved accuracy, regression rates, and F-score of 93.51%, 91.63%, and 90.64% respectively. To improve the experimental section of a deep learning study, we compared the performance of the proposed model against several established or simpler algorithms (baselines) in the literature such as K-Nearest Neighbors (K-NN), eXtreme Gradient Boosting (XGBoost), and support vector machine (SVM). This contextualizes the model's efficacy and demonstrates its advantage over existing methods. This study showcases how different sensors can support deep learning algorithms in the assessment of pavement performance over the long term.

Keywords: Structural Health Monitoring (SHM); long-term pavement performance; pavement sensors; Internet of Things (IoT); deep learning, convolutional neural network

1. Introduction

For a long time, the service life of Chinese pavements has been short, and it is difficult to reach the design life. The maintenance cycle of the pavement is short, which greatly wastes manpower, material, and financial resources. As early as 1996, Academician Sha Qinglin, based on the current status of asphalt pavement structure and material use on China's highways at that time, was inspired by the "Pavement Long-term Performance Research" project in the United States. In order to further verify the long-term impact of key technical indicators (mainly bending and traffic load) in asphalt pavement design on performance, he proposed to carry out the "Semi-rigid base asphalt pavement long-term performance observation" research.

Under the leadership of Academician Sha, the research team investigated the use status of more than 30 highways and trunk roads in 18 provinces and cities across the country within 3 months, and collected a large amount of disease data, such as rutting and cracks. At the same time, the pavement long-term performance information system software was compiled, and two special observation sections (SPS) were set up in Guangdong and Xinjiang to serve the long-term performance observation of asphalt pavements [1–4].

From 2006 to 2010, the Highway Research Institute of the Ministry of Transport undertook a scientific and technological project of the Western Science and Technology Project Management Center of the Ministry of Transport, namely, the "Research on Long-term Performance of Asphalt Pavements on Highways (Phase I)". The project targeted the most important asphalt pavement structure of China's highways. Through field investigation, accelerated loading test, pavement performance observation, theoretical analysis, and experience summary, a systematic study was conducted on the factors affecting the long-term performance of asphalt pavements on Chinese highways, the comprehensive test and verification system, and the long-term performance observation system [5–9]. A research framework system affecting the long-term performance of asphalt pavements on highways was constructed, a comprehensive test research and verification system based on mechanical properties and asphalt pavement performance was proposed, a long-term performance observation system for asphalt pavements on China highways including zoning layout and detection elements was established, methods and models for the research on the long-term performance of asphalt pavements were proposed, and a preliminary long-term observation database for asphalt pavements was established, which provided good data support and theoretical basis for how to conduct long-term performance research on asphalt pavements in China [10, 11].

1.1. Related work

1.1.1. Pavement research role

In 2013, the Ministry of Transport issued key scientific research tasks for 2014, among which "Long-term Performance Research of Asphalt Pavements" was a priority support direction. As the main undertaker of the project, the Ministry of Transport conducted a five-year long-term performance observation and research on asphalt pavements in the national highway network, comprehensively collected performance data of typical asphalt pavements in China, and conducted in-depth research on the main influencing factors and changing patterns of long-term performance of asphalt pavements in China [12, 13].

Although China's highway infrastructure is developing rapidly, the latest "National Highway Network Plan (2013–2030)" shows that China's total highway mileage will reach about 5.8 million km in the future, including about 400,000 km of national trunk roads. However, the lack of accumulation of diversified data on highway infrastructure has greatly restricted the sustainable development of China's highway industry.

Xinjiang is still in a blank state in the research of long-term pavement performance.

Since the 1980s, scientific researchers have carried out a lot of research on the technical difficulties of highway construction in our region, especially in the research of saline soil diseases, sand damage, snow damage, and pavement diseases in heavy traffic environments. Corresponding research results have been achieved, but no research has been carried out on the long-term performance of pavements [14–16].

1.1.2. Deep learning-based damage detection

In the reported works, the authors employed different DNNs for structural damage Identification. Certain works investigated the possibility of automated damage detection or explored the ability to monitor the Performance of the structural material. Zhang et al. [17] detected the damage automatically in the lining concrete under freeze-thaw cycling by using a deep hybrid neural network-aided electromechanical impedance method. Ai et al. [18] identified the damage in concrete structures by using Deep learning of electromechanical impedance. Sapidis et al. [19] used a novel approach to monitoring the performance of carbon-fiber-reinforced polymer retrofitting in reinforced concrete beam-column joints. Ai et al. [20] identified the compressive stress and damage in a concrete specimen using a convolutional neural network that learned electromechanical admittance. Sapidis et al. [21] used a deep learning approach for autonomous compression damage in fiber-reinforced concrete based on piezoelectric lead zirconate titanate transducers. Ai and Mo [22] predicted unknown compressive stress/damage in concrete structures using 3D convolutional neural network-based deep learning of raw electromechanical admittance signals.

1.1.3. Pavement monitoring

The long-term performance demonstration point observation system of the roadbed and pavement mainly uses an online monitoring system to monitor the road structure online. The long-term online monitoring system for the roadbed and pavement is an automated monitoring system dedicated to civil engineering projects, integrating test instruments, data acquisition and processing systems, lightning protection systems, and communication systems. The monitoring system used should combine the world's first-class data acquisition core technology with the latest modern electronic information technology, have the advantages of high stability and high anti-interference ability, and have the characteristics of high quality, strong adaptability, and wide compatibility. It should be in the leading position in the field of civil engineering monitoring and has been applied in many large-scale scientific research projects at home and abroad.

We can follow the development of road damage detection approaches during the last decade in **Figure 1**.

By establishing an advanced and practical pavement health and safety monitoring system based on deep learning model for the pavement, we can grasp the pavement operation status in real time and realize real-time safety alarm of pavement service level; rationally allocate pavement maintenance resources, provide scientific and technological basis for reducing pavement operation and maintenance costs, and ensure that the pavement inspection and maintenance strategy is targeted, timely and efficient.

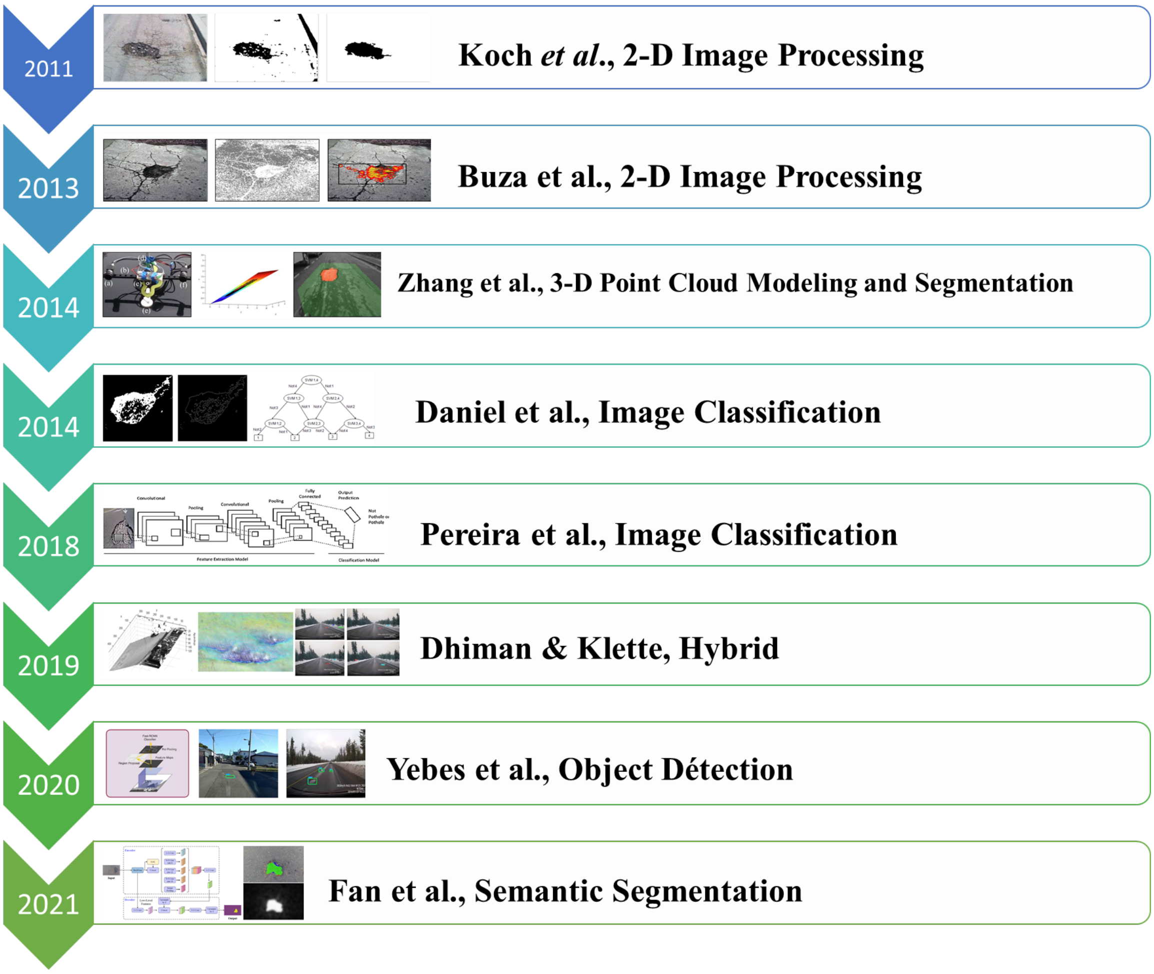


Figure 1. The development of pavement damage detection approaches during last decade.

2. Methodology

This study implemented a structured, multi-step methodology that integrates an advanced pavement sensory system, data acquisition, meticulous preprocessing, strategic feature selection, and sophisticated predictive modeling using a novel deep learning algorithm based on CNN. The overarching objective was to develop accurate regression models capable of predicting long-term pavement performance based on highly accurate road surface sensory data. A comparison of the performance of the proposed model against several established or simpler algorithms (baselines) such as K-Nearest Neighbors (K-NN), eXtreme Gradient Boosting (XGBoost), and support vector machine (SVM) is established. The entire methodological framework is summarized in **Figure 2**.

Monitoring system description

The schematic description of the pavement monitoring is illustrated in **Figure 3**. For automatic monitoring of asphalt pavement damage, we will use the requirements in **Figure 3** for the operation period of the pavement damage to realize the automatic acquisition of parameters such as the pavement damage and pavement pothole, and to have intelligent analysis, evaluation, and critical threshold alarm for the safety status of various structures. Specifically included in **Table 1**.

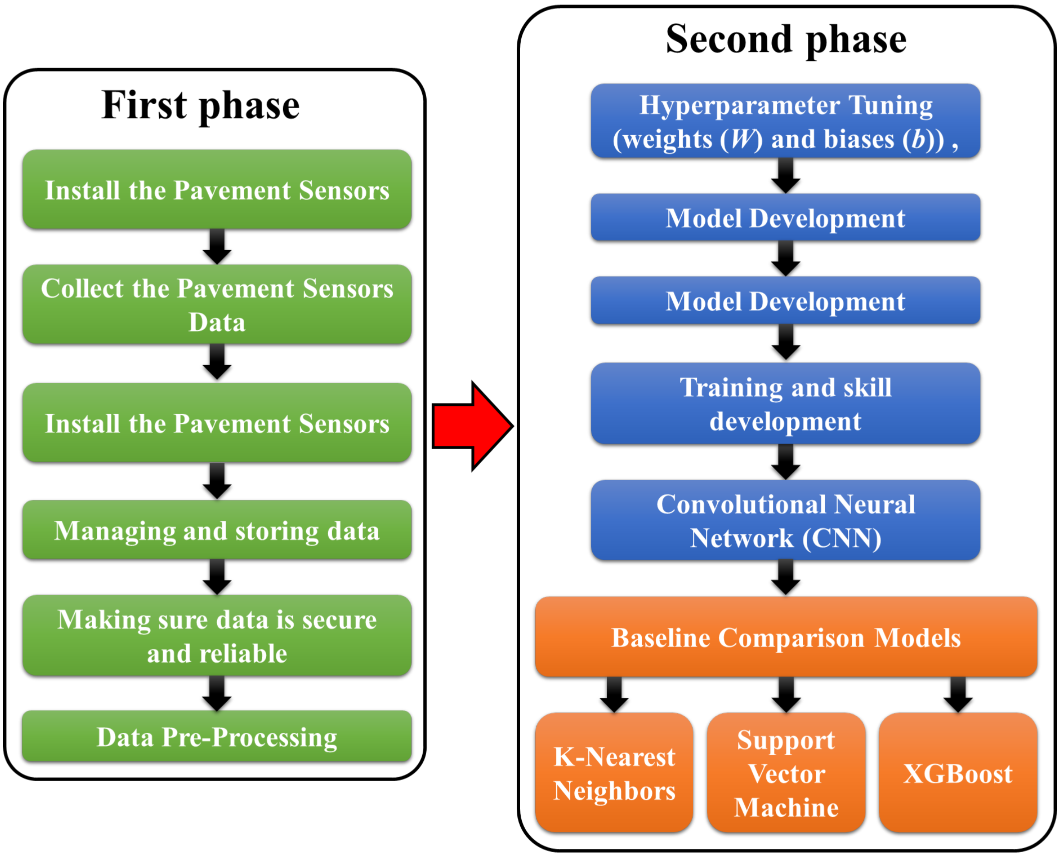


Figure 2. The flowchart of proposed pavement monitoring system.

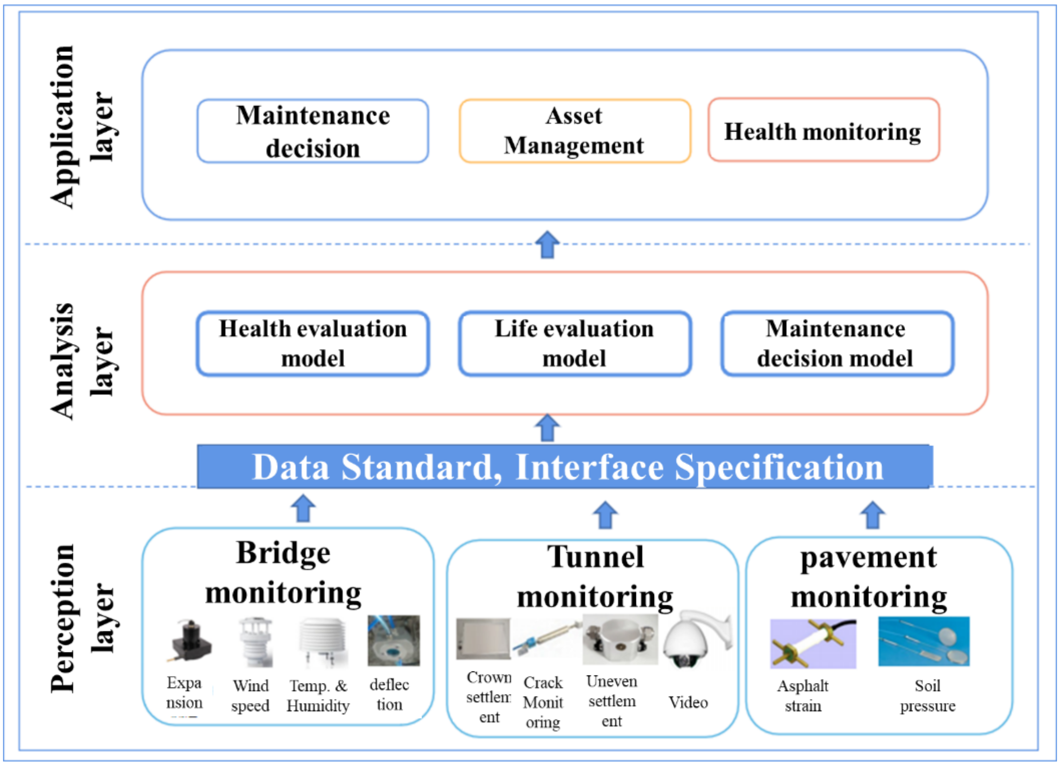
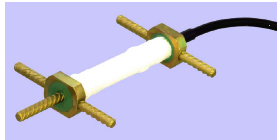
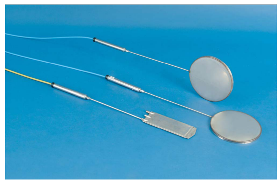
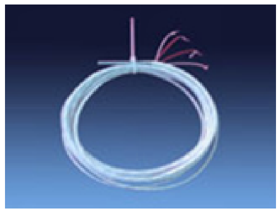
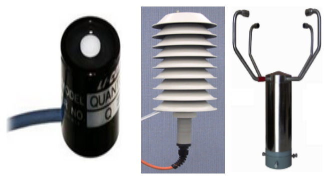


Figure 3. The schematic description of the monitoring system design.

Table 1. The pavement monitoring system description.

Monitoring system	Description	Sensor
Asphalt strain monitoring	It is laid out at the bottom of the asphalt layer to obtain the dynamic bending and tensile strain data of the bottom of the asphalt mixture layer. The strain gauges are arranged horizontally, with longitudinal and transverse directions to measure the strain in the vertical direction.	
Concrete strain monitoring	The surface layer of the water-stabilizing layer below the asphalt layer is arranged corresponding to the asphalt strain test position to obtain the three-dimensional stress dynamic response data of the road base.	
Earth pressure monitoring	Used to measure the vertical pressure of the roadbed layer under dynamic load, the pressure cell is arranged on the top and lower surface of the roadbed layer, located in the center of the inner wheel track, because it is expected that the stress generated by the wheel on the pavement structure is the greatest at this position.	
Soil moisture monitoring	Soil moisture sensors are placed in the soil layer of the external roadbed to measure the moisture content of the soil layer.	
Multi-point displacement monitoring	Measure the settlement displacement of the water-stable layer and the roadbed layer. Arrange multiple settlement meters on the shoulders outside the carriageway to measure the displacement changes of the base layer.	
Temperature monitoring	On the hard shoulder outside the lane, measure in layers from the asphalt layer to the roadbed soil layer.	
Dynamic weighing	Used to measure the size and type of load, the placement of the sensor should take into account the wheel offset and vehicle type during measurement. It can detect the axle weight, total weight, wheelbase, speed, length, passing time of vehicles with a speed of 0 to 200 km/h, automatically take the license plate, and automatically separate the vehicle.	
Weather Information	Collect various meteorological information at the monitoring points, mainly including temperature, humidity, wind speed, wind direction, rainfall, air pressure, total radiation, illuminance and ultraviolet intensity.	

3. The practical work

This study focuses on a highway in the Xinjiang Region that stretches about 106.6 km. It runs from 88°24′00″ to 89°57′00″ east longitude and 42°48′00″ to 43°12′00″ north latitude. In simpler terms, it travels in an east-west direction.

In Structural Health Monitoring, figuring out the features is super important for spotting how structures are doing, checking their health, and catching any possible damage. We use some cool techniques to handle data from sensors that measure things like vibrations, displacements, or strains. This helps us pick out important features that show how a structure behaves over time.

3.1. The pavement sensors installation

To track how roads hold up over time, we can hide different sensors in various spots, like the road surface, base, and even the slope. This sets up a sensor network using IoT tech, which helps us keep a close eye on environmental conditions—just look at **Figure 4**. For the asphalt roads in Xinjiang, we mainly focus on monitoring stuff like asphalt strain, concrete strain, soil pressure, moisture, shifts in the ground, and temperature of the soil. Plus, we keep tabs on the dynamic load weight of the pavement and weather details.

Figure 4. Sensors and equipment installation.

For the road surface temperature, we use an infrared detector, and for checking road conditions, there's a fancy infrared laser setup. The best part? We don't have to cut into the road, which means less risk of causing any damage. This non-contact method lets us do the job without closing the road, making it a lot safer and easier to install.

To install pavement strain sensors, we need to prepare the surface really well first. Then, create a specific slot in the road for the sensor. After that, carefully fit the sensor in place, using leveling aids to make sure it's even and aligned. Next, secure the wire conduit and finish up by grouting or potting the sensor to protect it and ensure a solid attachment. And don't forget to keep everything clean and sealed properly to stop any water from getting in and to keep the readings accurate.

3.2. The pavement sensors calibration

When it comes to the analysis, it's important to remember that pavements are influenced by a variety of factors. So, we really need to run a proper calibration to check the data from the monitoring system and get a better understanding of how the pavement is performing. This calibration is all about looking at the pavement's overall behavior, especially focusing on key elements like the weight and position of the loads applied on the surface and the pavement's temperature. To do this, we conducted calibration tests using a falling weight deflectometer (FWD) while heavy vehicles with known weights drove over the monitoring system.

The initial tests were done with the FWD, as you can see in **Figure 5**. The goal here was to assess how the pavement reacted under different temperatures and load conditions.

Figure 5. Calibration tests.

In total, we ran 6 test campaigns throughout the day, targeting various temperatures. Each campaign had 4 different positions, making it a total of 24. For each of those positions, we applied 3 increasingly heavier loads based on the height from which the weight fell.

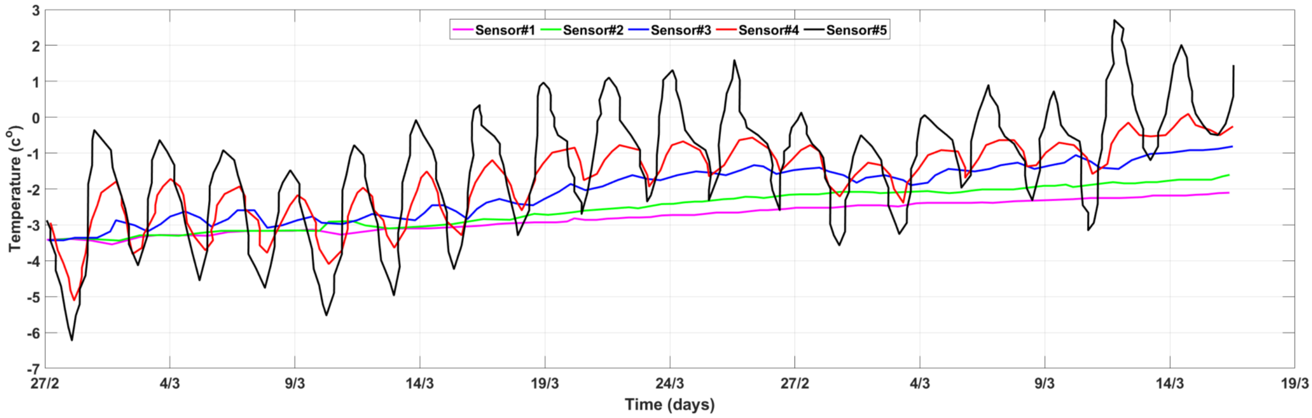
3.3. The pavement sensors data

Figure 6a shows how the temperature has changed over time. You can see some big swings, going from around −6 °C to about 2.5 °C. This kind of temperature variation can really affect how pavement materials behave, causing them to expand or contract. It's something we definitely need to keep in mind when looking at asphalt strain. Then there's **Figure 6b**, which tells a similar story, but this time with humidity levels changing quite a bit, too.

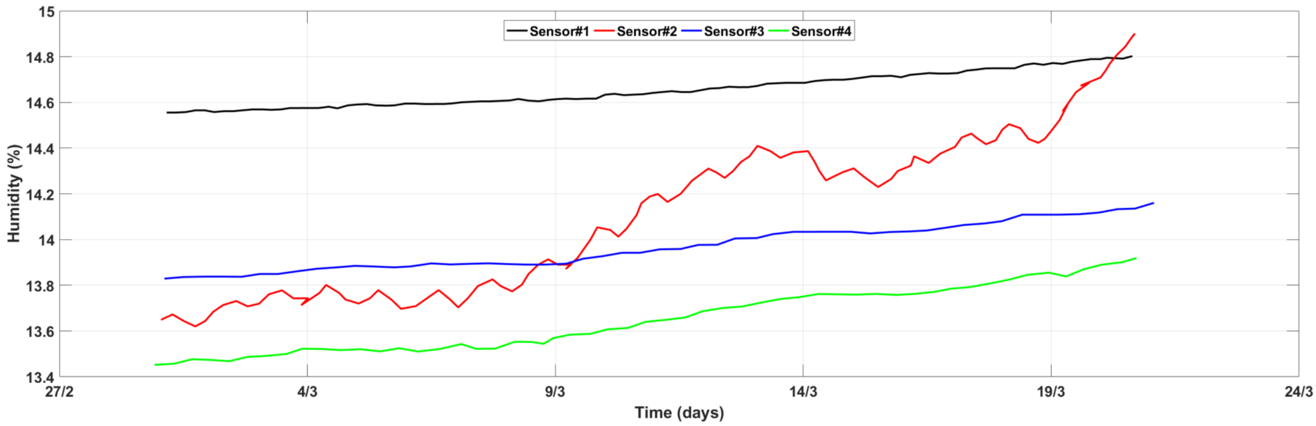
Moving on to **Figure 6c**, it gives us a closer look at asphalt strain throughout the monitoring period. The x-axis shows the dates, from 2/27 to 3/19, and the y-axis shows strain values that range between −300 and 400 units. Those green lines represent what we'd typically expect for different sensors when everything's running smoothly. **Figure 6d** focuses on vertical strain during the same time, and **Figure 6e** looks at the strain in concrete (like water stability) during that same stretch. By reviewing all this data, we can come up with maintenance plans to tackle any issues that might come from strain, helping keep the pavement safe and sound in the long run. We noticed some noise in the strain data, so we'll need to clean that up before digging deeper.

Now, **Figure 6f** tracks the average pressure over time, giving us a sense of the general pressure the pavement was under during the monitoring period. Again, the x-axis shows the dates from 2/27 to 3/19, and the y-axis displays pressure values between about 10 and 40 MPa. This range shows what kind of pressure the pavement experienced on average. The green lines show what's typical for the pressure sensors under normal circumstances.

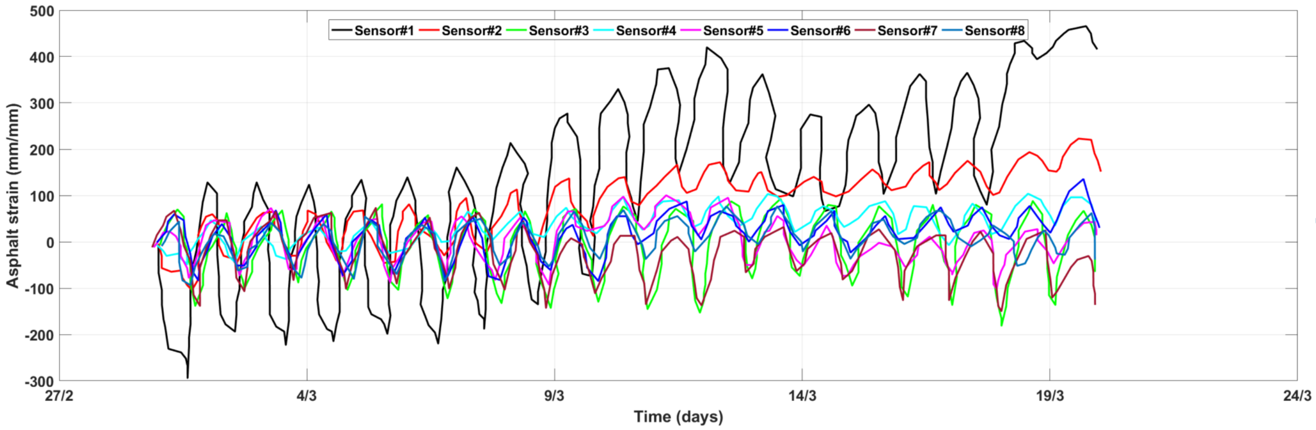
Lastly, **Figure 6g** measures how much the water-stable layer and the roadbed layer have settled. We've got a bunch of settlement meters set up on the shoulders outside the roadway to keep tabs on any changes in the base layer.



(a) Temperature.

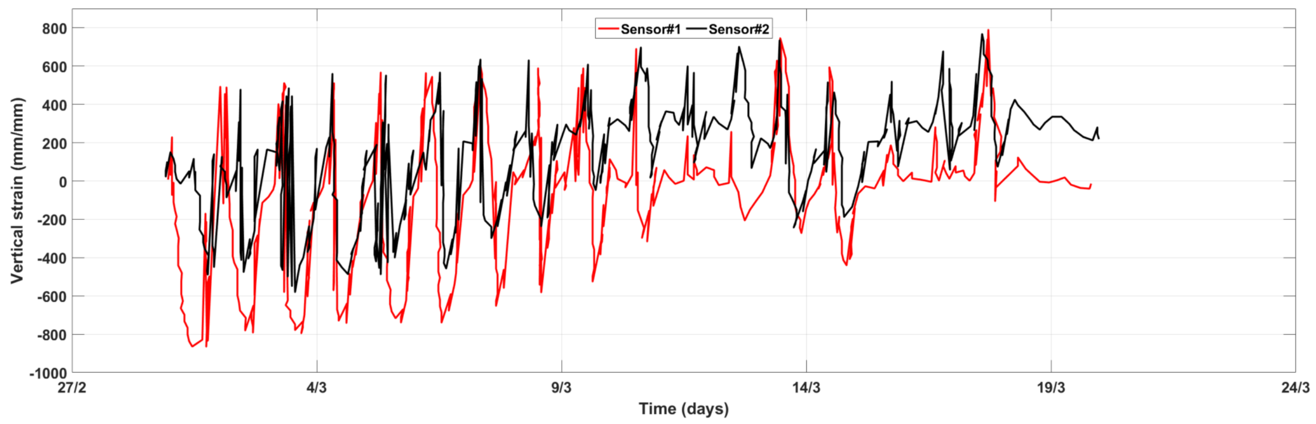


(b) Humidity.

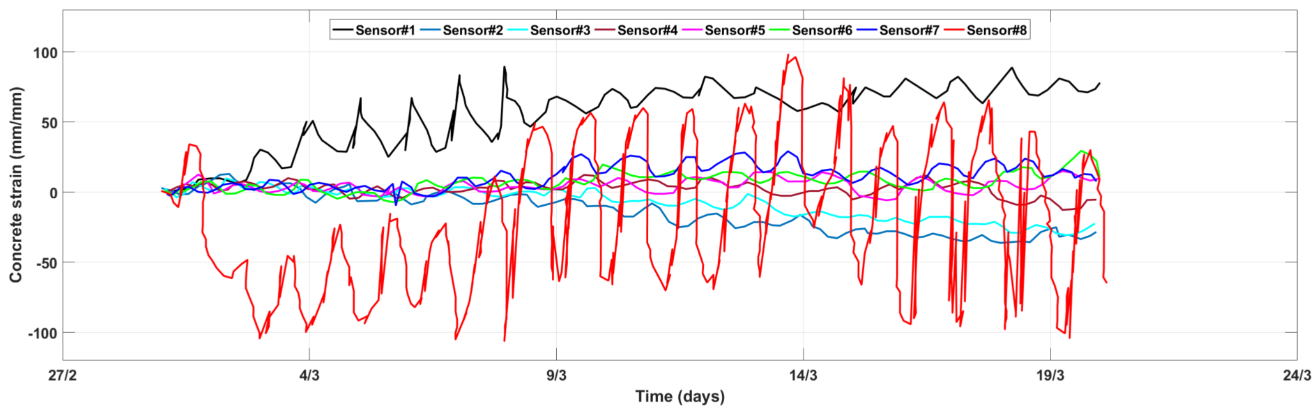


(c) strain.

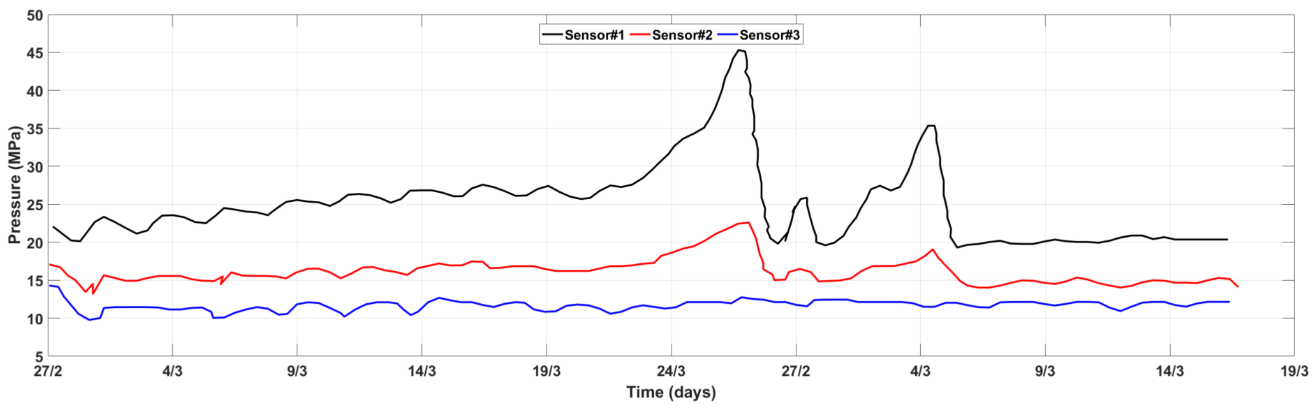
Figure 6. *Cont.*



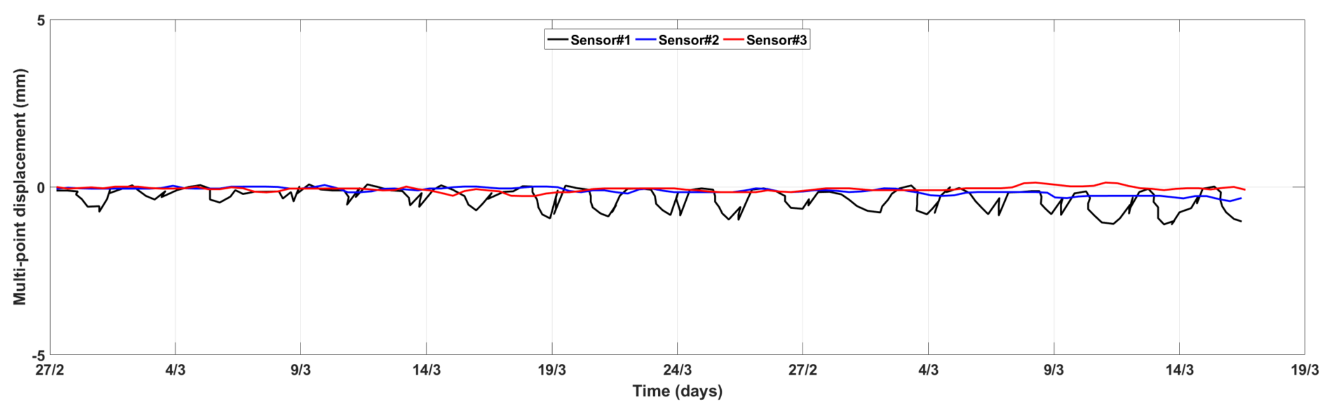
(d) Vertical strain.



(e) Concrete strain.



(f) Pressure.



(g) Multi-point displacement.

Figure 6. The pavement sensors data.

4. Convolutional neural network (CNN)

A convolutional neural network (CNN) is a type of deep learning model particularly well-suited for processing data with a grid-like topology, such as images and videos. CNNs excel at automatically learning features from raw input data, eliminating the need for manual feature extraction. They are widely used in computer vision tasks like image recognition, object detection, and image segmentation, and can also be adapted for audio and other signal processing tasks [23,24].

4.1. CNN architecture for pavement displacement prediction

We've set up a multilayer neural network to build a CNN model aimed at predicting pavement performance based on sensor data from the pavement. The network is organized and trained systematically to enhance the generalization of this CNN model, helping us discover an effective CNN architecture.

This proposed CNN architecture, featuring sequential hidden layers, is illustrated in **Figure 7**. We've included fully-connected layers between the input (features) and output layers (what we're predicting) to help with extracting higher-level features during training. By using weights (W) and biases (b), the CNN learns to pick up more useful nonlinear information.

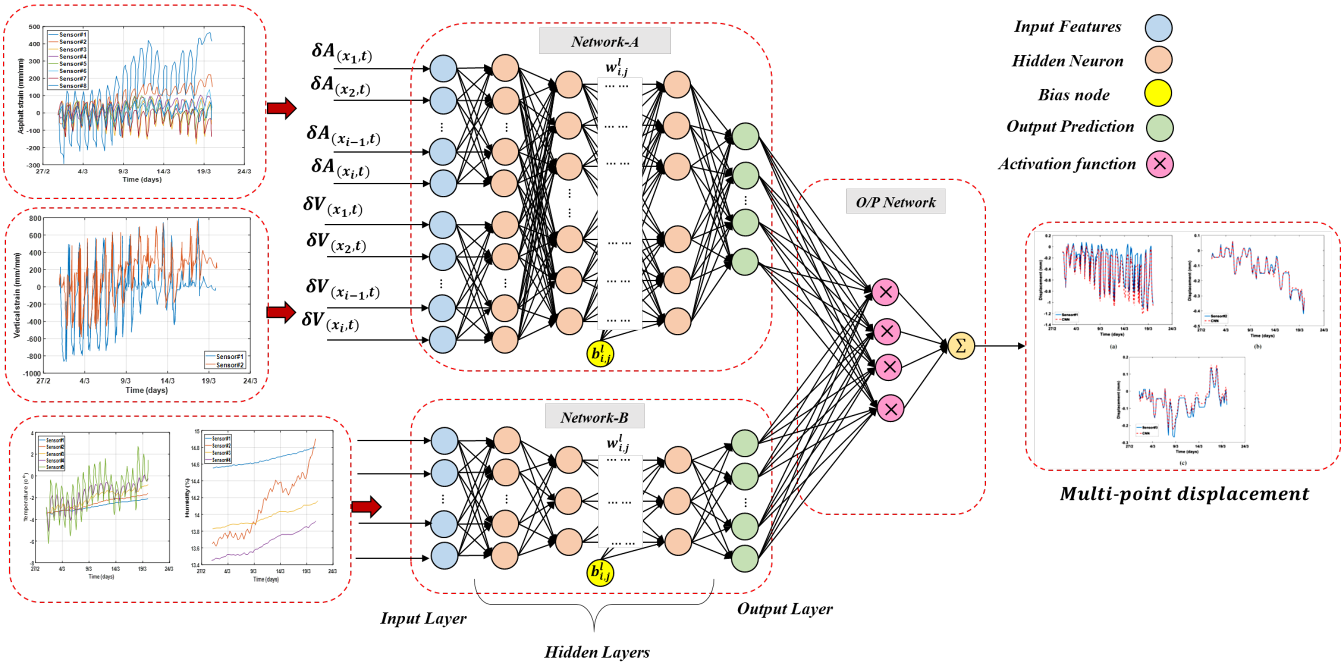


Figure 7. The fully-connected layers-type architecture of the proposed CNN.

To pull features from the pavement sensors data, we use one-dimensional convolution and mean pooling operations. Our fully connected neural network has six hidden layers: the first three layers have 502 neurons each, while the last three have 251. We're applying rectified linear units as the activation function for both the convolutional and fully connected layers. This process in our proposed CNN is outlined as follows:

$$\mathbf{x}_j^l = f\left(\sum_i \mathbf{x}_i^{l-1}\mathbf{w}_{ij}^l + b_j^l\right) \tag{1}$$

where x_j^l is the ith output map in layer l; x_i^{l-1} is the ith output map in layer $l-1$; w_{ij}^l is the weight; b_j^l is the bias; $f(\cdot)$ is a nonlinear function that is applied component-wise.

In **Figure 8**, you can see the basic setup of the convolution layers we used in this study, which also includes the sub-sampling layer (pooling layer S1, S2). One of the convolution layers C1, C2 consists of six feature maps.

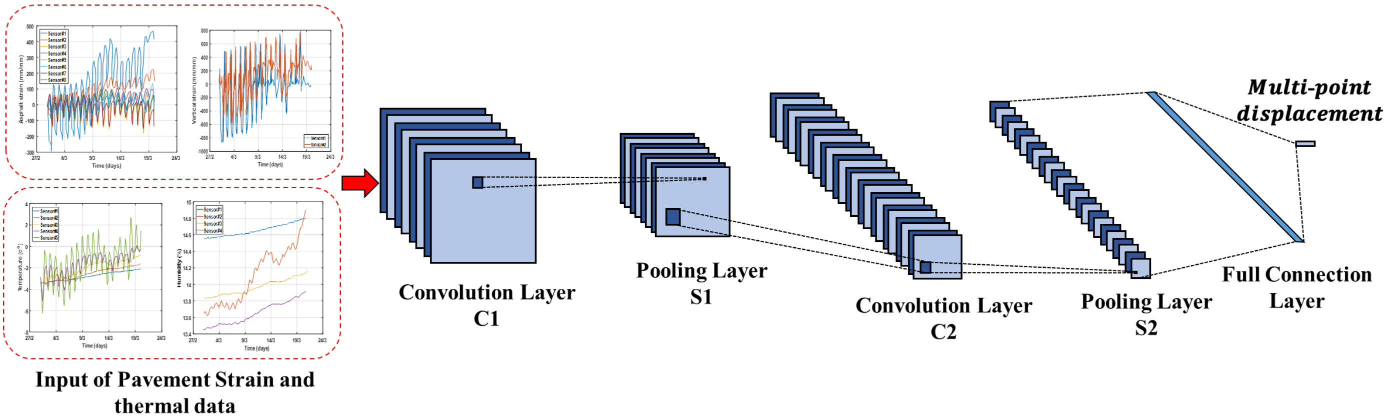


Figure 8. The architecture of a typical CNN.

The detailed settings for the convolution layer show the first convolutional layer C1, the first sub-sampling layer S1, and similar setups for the following layers C2 and S2, as you can see in **Table 2**.

Table 2. Detailed settings of the convolution layers.

Layer	Kernel size	Number of parameters	Number of connection
C1	8 × 8	148	5,695,040
S1	4 × 8	4	260
C2	8 × 8	4	260
S2	4 × 4	4	260

4.2. Training, validation, and test sets

For this research, we chose mean square error (MSE) to optimize network parameters like weights and biases in the layers. During training, we look at cluster features at different times and positions to fine-tune the network parameters, which helps control how many hidden layers change based on the training results. After running several test iterations, we get satisfactory outputs from the network, and it stops training when the MSE stabilizes at a low value.

So, we've got this method that uses some flexible parameters and features for training and testing, and you can check it out in **Figure 9**. **Figure 10** lays out how the CNN setup works, along with the training and testing models. If you look at **Figure 11**, it shows how well the CNN has been performing during training. By the way, when we say 'Epoch', it just means one complete pass through the whole training data. You can find the key training parameters in **Table 3**, and the MATLAB code steps for training and evaluating the RNN are in **Algorithm 1**.

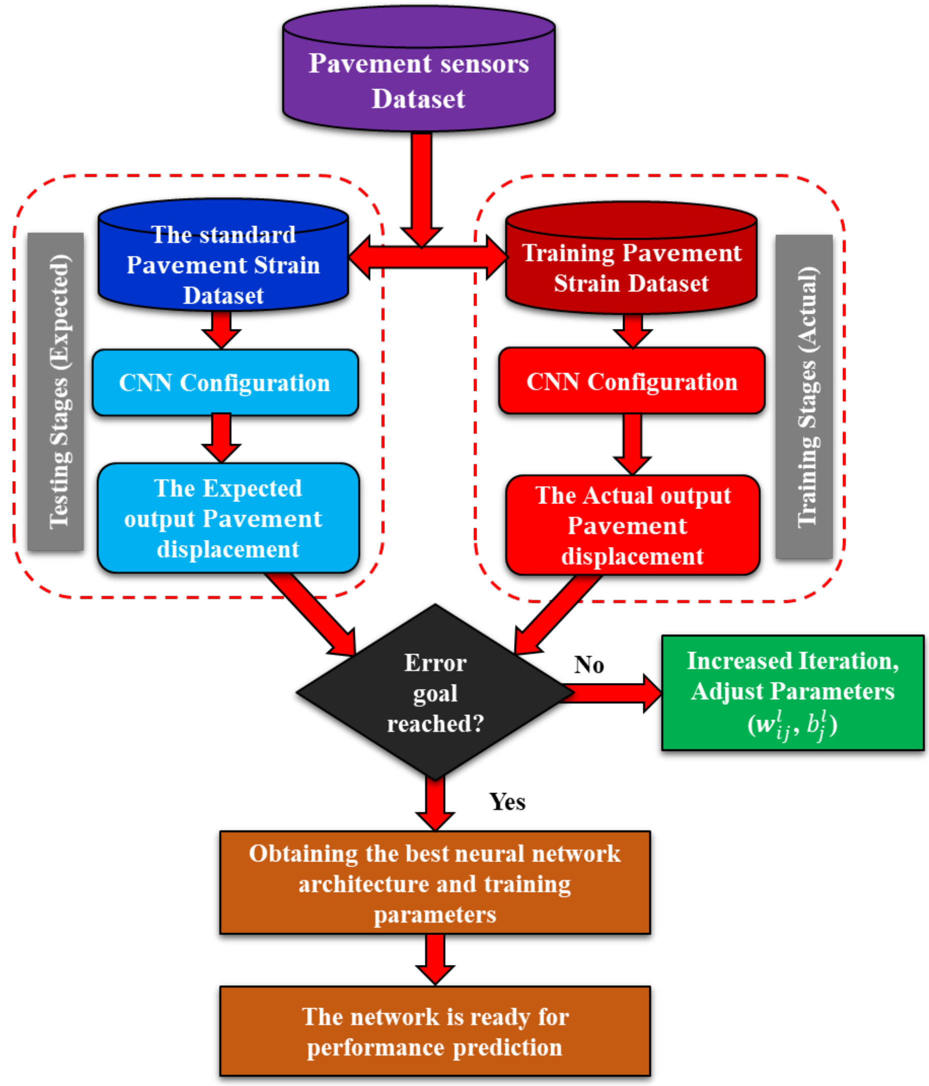


Figure 9. The architecture of the proposed CNN model for pavement displacement prediction.

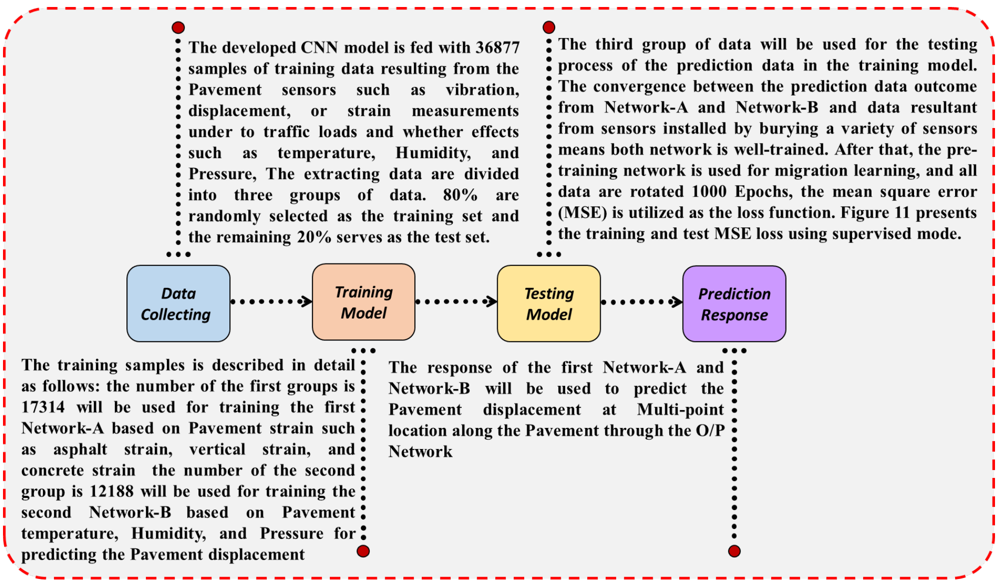


Figure 10. The steps of CNN training to estimate the pavement displacement.

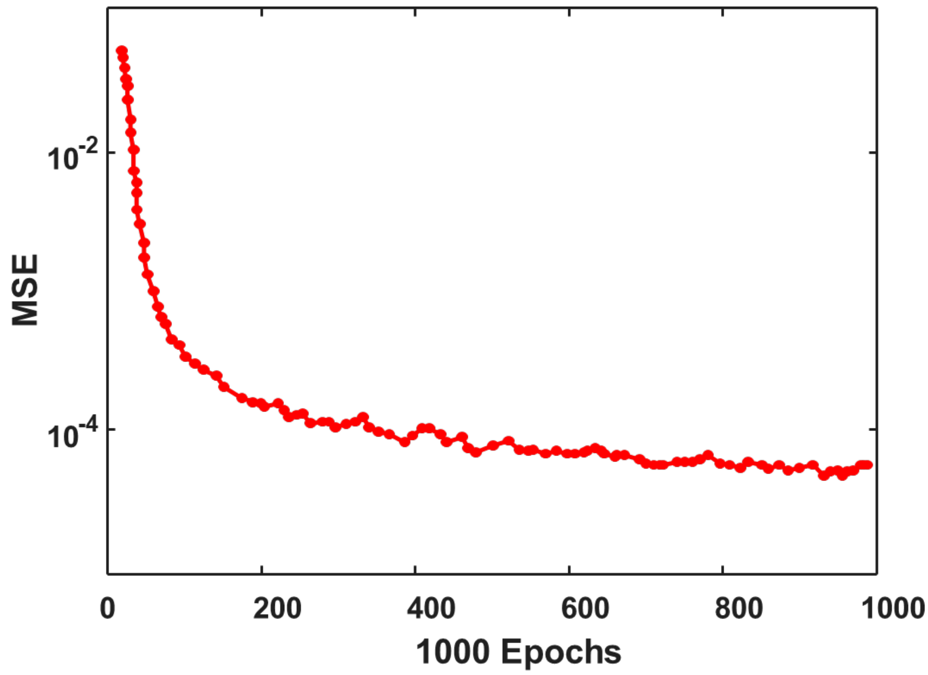


Figure 11. CNN training performance.

Table 3. CNN key parameters.

Training time	Gauge	Training rate	Attenuation factor
102 sec	42	10^{-4}	10^{-6}

Algorithm 1. Training, and testing of proposed CNN.

input: W: Network parameter matrix weight w_{ij} and bias b_j
output: score of CNN trained model on the structure images for crack detection
let f be the feature set 3d matrix
  for i in the dataset do
    let f_i be the feature set matrix of sample l
      for j in i do
      $V_i \leftarrow vectorize_{(j,w)}$
      append V_i to f_i
      append f_i to f
      $f_{train}, f_{test}, l_{train}, l_{test} \leftarrow$ the split feature set and prediction into train subset and test subset
      $M \leftarrow$ CNN (f_{train}, l_{train})
      score $\leftarrow$ evaluation (l, l_{test}, M)
    return score
  end for
end for

Moving on to **Figure 12**, it compares what the CNN predicted against the actual data from the pavement sensors at sensor #1, #2, and #3. From the figures, it's clear the CNN does a way better job at predicting in this case study, proving it can really model how the structure behaves.

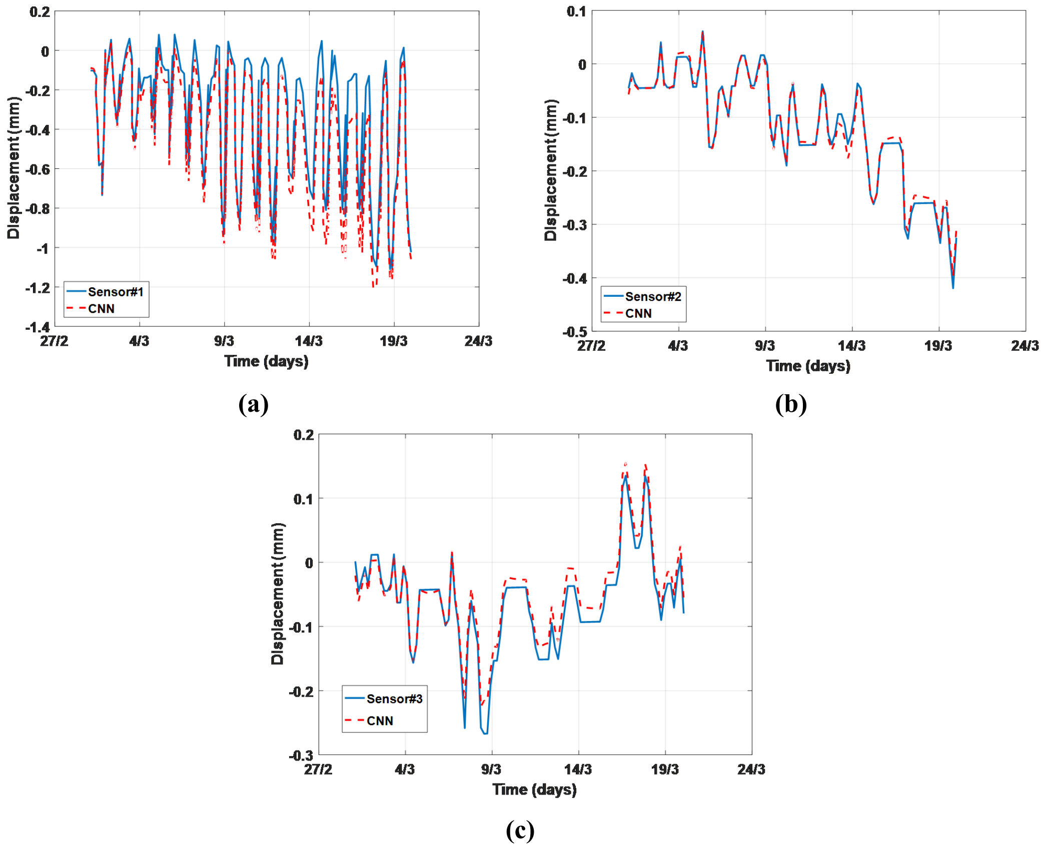


Figure 12. A comparison between CNN and pavement sensors experimental data of multi-point displacement for: **(a)** Sensor#1; **(b)** Sensor#2; **(c)** Sensor#3.

4.3. Proposed method accuracy and reliability evaluation

We look at four main things to check how well the proposed method is doing: the false negative rate (FNR), false positive rate (FPR), true negative rate (TNR), and true positive rate (TPR). Here's how we can tweak the performance based on those.

$$accuracy\ rate\ (P\%), = \frac{N_{TPR}}{N_{TPR} + N_{FPR}} \tag{2}$$

$$regression\ rate\ (R\%) = \frac{N_{TPR}}{N_{TPR} + N_{FNR}} \tag{3}$$

$$F\ score\ (F\%) = \frac{2N_{TPR}}{2N_{TPR} + N_{FNR} + N_{FPR}} \tag{4}$$

In this research, we prepared 40 datasets from pavement sensors to test things out, splitting them into 8 groups based on the output displacement in the pavement to get results for f_1, f_2 and so on up to f_8. This all happened after running a thousand iterations, or epochs, to check if the CNN really works. Overall, the performance metrics were pretty good, with $P\%$ at 93.51%, $R\%$ at 91.63%, and $F\%$ at 90.64%. So, it looks like this method can accurately detect displacement in the pavement. **Figure 13** shows how those $P\%$, $R\%$, and $F\%$ values changed over those 1000 epochs.

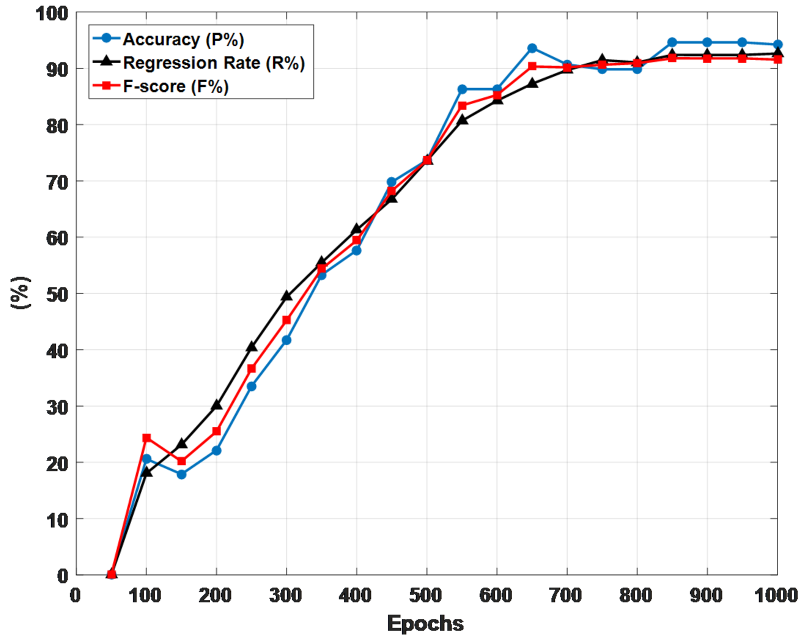
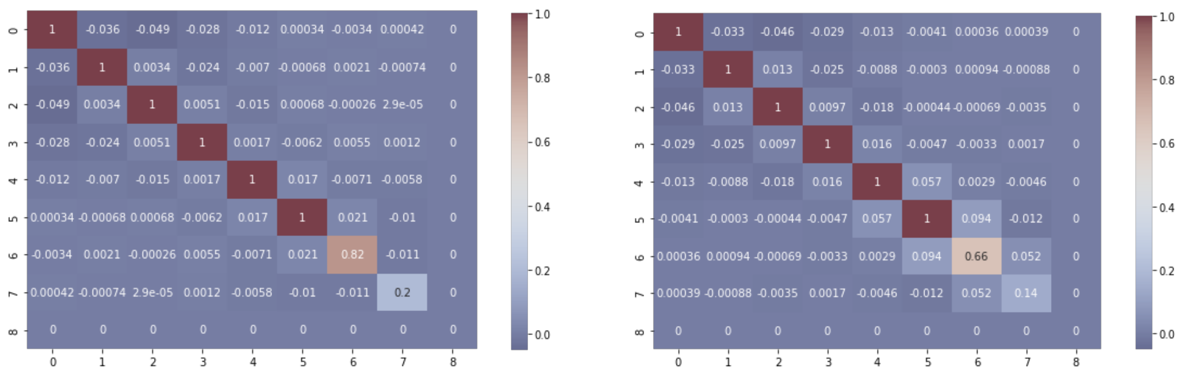


Figure 13. The training proceeded with a comparison based on the multi-point displacement in the pavement.

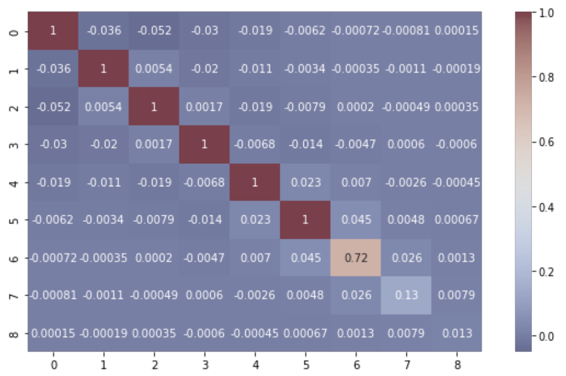
To improve the experimental section of a deep learning study, we compared the performance of the proposed model against several established or simpler algorithms (baselines) such as K-Nearest Neighbors (K-NN), eXtreme Gradient Boosting (XGBoost), support vector machine (SVM), or Linear Regression. This contextualizes the model's efficacy and demonstrates its advantage over existing methods. The results of multiple models are often compared using a confusion matrix, and a side-by-side look at baselines and the proposed model highlights how well the model can distinguish pavement monitoring.

In **Figure 14**, we can see how the CNN algorithm stacks up against three baselines methods (K-NN, XGBoost, and SVM) for predicting asphalt pavement distress by Yazdi and Dehnad [25]. It outlines how effectively each model identifies various scenarios for the CNN. Just so we know, any values below 1% are considered zero in these diagrams. **Figure 14** indicates that the CNN architecture is performing quite well, showing higher average accuracy and appearing to have the advantage.

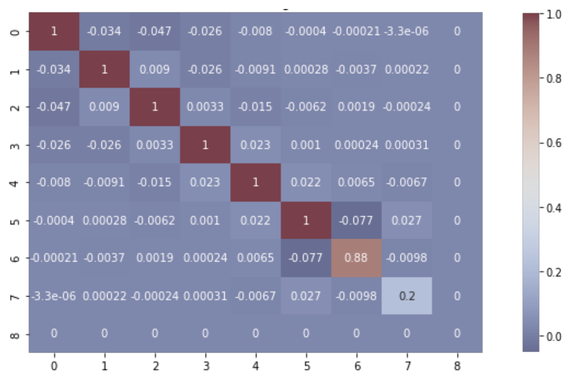


(a) CNN. **(b)** K-NN.

Figure 14. *Cont.*



(c) XGBoost.



(d) SVM.

Figure 14. The confusion matrices for of the CNN and baselines methods (K-NN, XGBoost, and SVM) used in literature.

5. Conclusion

This study focuses on implementing a mentoring system that uses technology for automatic monitoring of long-term pavement performance in the Xinjiang Region. Various sensors are embedded in different areas of the road, like the surface, base, and slope. With the help of deep learning algorithms, a sensor monitoring network powered by Internet of Things technology has been created. This setup allows for precise and ongoing observation of environmental conditions, physical states, mechanical responses, structural deformations, and more. Given the volume of data and the need for real-time analysis, a deep learning model using a Convolutional Neural Network (CNN) algorithm was trained on data collected from sensors monitoring temperature, humidity, pressure, asphalt strain, and displacement. The goal is to predict multi-point displacement in the pavement and identify issues of pavement damage. When we compared the CNN predictions with actual data from pavement sensors regarding multi-point displacement, it showed a significant improvement in prediction accuracy for this case study. The results highlighted the CNN's effectiveness in modeling structural behavior, achieving impressive metrics with $P\%$, $R\%$, and $F\%$ equal to 93.51%, 91.63%, and 90.64% respectively. The comparison of the CNN algorithm against three baseline methods (K-NN, XGBoost, and SVM) outlined how effectively pavement monitoring can be achieved using a confusion matrix and a side-by-side look at baselines, and the proposed model highlights how well the model can tell apart pavement monitoring. This study showcases how different sensors can support deep learning algorithms in the assessment of pavement performance over the long term. Future work should focus on incorporating additional data sources, enhancing real-time capabilities, employing advanced deep learning techniques, and fostering industry collaboration to further improve and standardize monitoring solutions.

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