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Deep Learning Network for Remote Monitoring of Thermal Exchange Tunnels

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Abstract

Monitoring and predicting ground settlement throughout tunnel construction is critical to ensuring the safe and accurate use of urban tunnel systems. The accurate and efficient diagnosis of such settlement can decrease hazards while improving the safety and dependability of these initiatives. However, typical tunnel inspection procedures are time-consuming, costly, and heavily reliant on human subjectivity. The trained model's accuracy was evaluated by comparing its findings across extended operating durations using the same and different thermal operational patterns as those utilized for training. Deep learning, one of the most powerful Artificial Intelligence approaches, is required for the tunnel's settlement predicting challenge. Nevertheless, deep neural networks frequently want huge quantities of training data. In the method we used, CNN-LSTM models were trained on datasets of various sizes and attributes. The results suggest that both of the proposed models may achieve a little inaccuracy under specific situations.

Keywords: Tunnel Construction, Deep learning, CNN-LSTM Models, Mean Square Errors, Evaluation Metrics.

1. Introduction

In recent years, the implementation of novel technologies has transformed monitoring and maintenance processes, particularly in critical facilities like tunnels. Tunnels, which are a form of subterranean space construction, have been extensively built over the last several

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decades to meet the increasing demand for transportation. Thermal exchange tunnels are structures that exchange heat between two environments, typically for heating or cooling. Remote monitoring of the thermal exchange tunnels requires the use of numerous technologies along with sensors to gather data and assure the tunnels' effective and safe operation. These tunnels are intended to exchange heat between different environments, such as tunnels for district cooling and heating systems. Accurate as well as real-time forecasting of tunnel face distortion enables site engineers apply suitable treatment to guarantee stability throughout the excavation around the rock [1].

Tunnels are vital infrastructure networks that hold numerous utility services such as water, power, gas, and telecommunications. Maintenance as well as inspection of such tunnels have always been difficult and time-consuming undertakings. However, because to improvements in smart networks of sensors, utilities tunnel operations are being transformed, resulting in improved productivity, safety, and cost-effectiveness.

The LSTM network has been successfully used in several fields, including pattern recognition, automated translation, audio and video processing analysis, traffic flow prediction, medicine, and more. It may be readily applied to the tunnel surface settling problem. LSTM network is a type of recurrent neural network, or RNN, that can handle sequential and time-series data. When used to remotely track the performance of thermal exchange tunnels, the LSTM networks may detect temporal relationships and patterns in the data.

The proposed prediction model is built on a hybrid deep learning (HDL) framework that includes a convolutional neural network (CNN) along with a long short-term memory (LSTM) as its base. In this research, we evaluate the proposed model based on the evaluation metrics such as RMSE and MSE.

2. Literature Review

The study's major purpose is to monitor and anticipate the deformation of the rocks around it during the building of rock tunnels. Accurate forecasts of tunnel deformations are considered critical for rock tunnel construction. The researchers suggested a transformer model that includes the building sequence in the positional embedding. The transformer model also incorporates an attention module, which is used to efficiently understand the high-dimensional association between tunnel face and adjacent deformation. This study utilizes LSTM and its attention enhanced model and then performs a comparison by considering the transformer model [2]

Although objective detection as well as segmentation techniques that use deep learning are frequently used in image processing, they are rarely employed in Infrared thermography (IRT). The research discusses deep-learning based image processing approaches for the identification of defects and detection utilising IRT. The primary goal of the research is to incorporate deep-learning (DL) models enabling autonomous thermal image interpretation in quality management (QM). Multiple deep Convolutional Neural Networks (CNNs) are utilised for defect identification.[3]

The research emphasizes the importance of improving the intelligent identification of ROV image data in order to identify siltation more effectively. Experimental findings on a siltation dataset show that the suggested technique has a classification accuracy of 97.2%, beating previous classifiers. The suggested technique may measure accuracy against model complexity, making it appropriate for systems with limited computational resources.[4]

The research provides a new computer vision-based technique for identifying concrete fractures. This vision-based strategy tries to overcome the limitations of touch sensors and decrease the number of false alerts. The architecture is intended to efficiently learn and extract characteristics from crack images. This high accuracy demonstrates the usefulness of the suggested vision-based technique for identifying concrete fractures.[5]

The study suggests a unique way for determining the most defective location in a hard rock sample. Motion thermogram data derived from laboratory observation of rockburst events is combined with a cutting-edge deep neural network technique, especially a regional convolutional network (Mask RCNN). This technique used depends on a regional convolutional network, especially Mask RCNN. Mask RCNN is well-known for its capacity to identify, localise, and segment images in computer vision.[6]

The suggested CNN-BiLSTM-based technique demonstrated extraordinary detection performance and resilience. It achieved an F1-score of more than 99% for location identification, as well as detection of varying heat release rates (HRRs), despite having sensors positioned more than 40 metres apart within the tunnel.[7]

3. Methodology

➢ LSTM

Hochreiter and Schmidhuber developed Long Short-Term Memory, an upgraded version of the recurrent neural network. LSTM is ideal for sequence prediction applications and excels in detecting long-term dependencies. A typical RNN contains a single hidden state that is updated over time, making it challenging for the neural network to develop long-term dependencies. LSTM networks can learn long-term relationships in sequential data, making them ideal for applications like language translation, recognition of speech, and time series forecasting.

LSTMs may be layered to form deep LSTM networks that can learn more complex patterns from sequential input. Each LSTM layer detects varying levels on abstraction and temporal relationships in the input data. The memory cell contains three gates namely input gate, forget gate, and output gate.

- **Input Gate**

The input gate determines what information goes in to each memory cell. It selectively modifies the cell's state based upon the current i/p as well as the previous steps' stored information. Priorly, the data is controlled using sigmoid function, the function filters the data to be remembered as same as forget gate do with inputs h_{t-1} and x_t. The tanh function is then used to construct a vector with an output range of -1 to +1, including all possible values between ht-1 and xt. Finally, the vector's values and the controlled values are added together to get relevant information.

- **Sigmoidal Activation Function:** The sigmoid function assists the model in determining whether data from the present input and the prior hidden state must be updated or discarded.

- **Tanh Activation Function:** The second component of the input gate is a tanh activation function. It also accepts the current input as well as the prior hidden state as input.

- **Forget Gate**

The forget gate determines the information that has to be removed in the memory cell. Moreover, it removes the no longer helpful data or information in the cell state. The inputs received by the gates, xt (input at current moment) and ht-1 (previous cell output), that are multiplied by weighted matrices before addition of bias. Provided, result is transferred via activation function, which returns a binary value. If output of cell state=0, particular piece of data has been forgotten, but output 1 retains the information for future use.

- **Output Gate**

The output gate determines the hidden state using the input sequence and information stored in the memory cell. It controls the flow of data form memory cells to outputs and aids in the capture of key characteristics for the job at hand.

The output gate extracts important information from the present cell state and presents it as an output. First, the cell is transformed into a vector using the tanh function. The information is then controlled utilising the sigmoid function and filtered by what needs to be remembered through the inputs ht-1 and xt. Finally, the outcomes of the vector as well as the controlled values are multiplied and provided as an input and an output to the following cell.

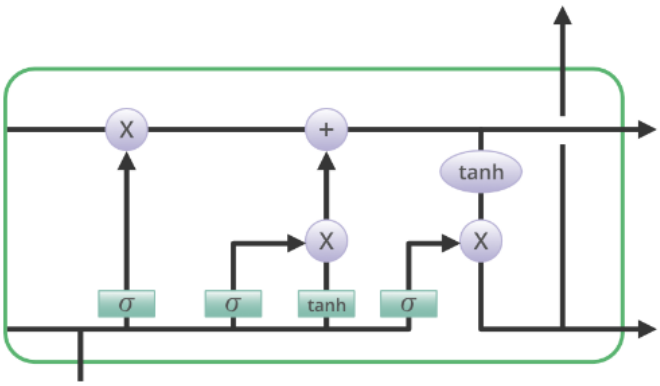

Figure 1. LSTM Model [8]

- **Advantages**

Long-term dependencies may be recorded using LSTM networks. They have a memory cell that can store data for an extended period of time.

When standard RNNs are trained over extended sequences, disappearing, and bursting gradients occur. This issue is addressed by LSTM networks, which employ a gating mechanism which selectively recalls and forgets information.

- **CNN-LSTM**

A CNN analyses sequence data through the use of convolutional input filters. CNN learns characteristics from both the spatial as well as temporal dimensions. An LSTM network analyses sequence of data through repeating multiple steps along with determining long-term relationships within them. CNN-LSTM neural network uses layers of LSTM in order to learn from training data. The network is trained using audio data, first auditory-based spectrogram are extracted with the help of raw data and then the network is trained.

A CNN-LSTM model combines CNN layers to extract features from input data with LSTM layers for sequence prediction. CNN-LSTMs are commonly used for activity identification, image labeling, and video labeling. Their shared qualities include being designed for the use of graphical time series prediction issues.

- **Advantages**

CNNs are good at detecting spatial hierarchies of characteristics in input data. They may develop low-level features over early levels and then proceed to more complicated, high-level characteristics in later layers. Combining CNNs with LSTMs allows for hierarchical feature extraction in both time and spatial dimensions.

By combining both architectures, the model can learn and recognise patterns including both temporal and spatial information, making it suited for tasks.

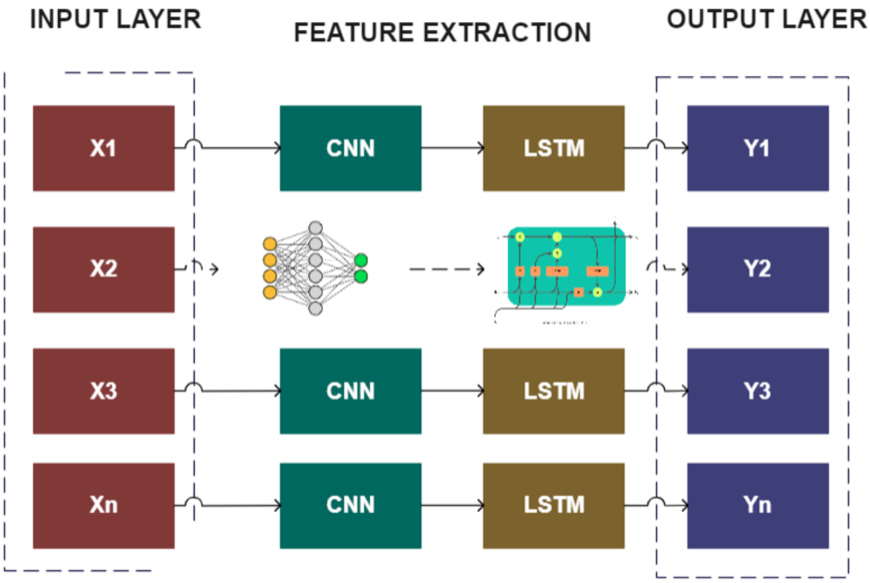

Figure 2. Architecture of CNN-LSTM

3.1 Proposed Method

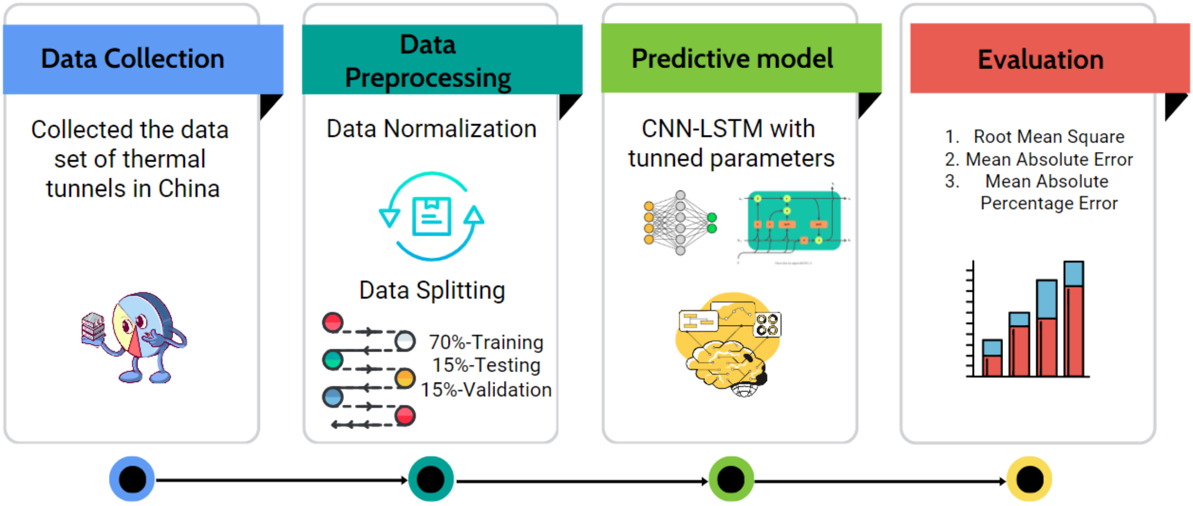

Figure 3. Process Flow of the Proposed Work

- **Data Collection**

The dataset is the data's collected within a tunnel built by Ningbo Metro Line 3 in Ningbo, China.[9]

	0.41	-11.54	PC0001	NBDT	NINGBO1	D149-2	pt01	149	0	3	0.1
	Category	Category	Category	Category	Category	Category	Category	Category	Number (Integer)	Number (Integer)	Number
	Other 74.4%	Other 93.9%	PC0003 42.4%	WY-HD 23.8%	NINGBO1 23.1%	Other 92.2%	pt01 95.9%	Other 65.6%			
	0.0 1.4%	0.0 2.4%	PC0001 23.1%	NBDT 23.1%	blank 21.2%	D205-8 0.3%	pt02 2.6%	205 3%			
	Other 24.2%	Other 3.8%	Other 34.5%	Other 53.1%	Other 55.7%	Other 7.6%	pt03 1.4%	Other 31.4%	-17.0 58.0	1 3	0.0
4	Other	Other	PC0001	NBDT	NINGBO1	Other	pt01	Other	0.0	2	2.5
5	Other	Other	PC0001	NBDT	NINGBO1	Other	pt01	157	0.0	1	35.0
6	Other	Other	PC0001	NBDT	NINGBO1	Other	pt01	157	0.0	1	30.0
7	Other	Other	PC0001	NBDT	NINGBO1	Other	pt01	157	0.0	1	25.0
8	Other	Other	PC0001	NBDT	NINGBO1	Other	pt01	157	0.0	1	15.0
9	Other	Other	PC0001	NBDT	NINGBO1	Other	pt01	157	0.0	1	10.0
10	Other	Other	PC0001	NBDT	NINGBO1	Other	pt01	157	0.0	1	5.0
11	Other	Other	PC0001	NBDT	NINGBO1	Other	pt01	157	0.0	1	2.5
12	-0.08	Other	PC0001	NBDT	NINGBO1	Other	pt01	157	0.0	3	0.0
13	Other	Other	PC0001	NBDT	NINGBO1	Other	pt01	157	0.0	2	2.5
14	0.16	Other	PC0001	NBDT	NINGBO1	Other	pt01	157	0.0	1	5.0

Figure 4. Proposed Dataset

- **Preprocessing**

Following data gathering, the next process would be the pre-processing of subjected dataset. The primary goal of pre-processing step is to create and transform raw data to a formatted one for the proposed model. Implementing pre-processing is critical for deep learning models because it improves the accuracy of the model by increasing quality of data and retrieving essential information's. This work included a variety of data pre-processing approaches, ranging from data normalization to dataset splitting.

- **Data Normalization**

The datasets utilised in this study are from several sources, with varying units and scales. These dataset discrepancies may have an impact on HDL's performance throughout the learning process, or worse, raise the generalisation error. To circumvent this problem, every variable in the dataset needed to be scaled or normalised. Furthermore, this can increase the efficiency of model because every input parameter have been adapted to a standard range.

- **Dataset Splitting**

Input dataset needs to be properly collected and separated into three datasets: training, validation, and testing. The normal split ratios depend on the size of a dataset, however it is standard practice to utilize near 70-80% of the data in training, 10-15% in validation, and the balance of 10-15% for testing.

- **Model Approach**

- The suggested technique consists of four steps: data collecting, data pre-processing, CNN-LSTM model building, and model assessment using LSTM.
- The CNN-LSTM design had numerous layers. The 1st layer has two stack convolutional layer, both contain activation function that is a rectified linear unit (ReLU).
- Next is the max-pooling along with flattening layers.
- Followed by a stack of LSTM layers using activating function ReLU .
- The output layer was formed by connecting thick layers. These layers have Leaky ReLU as an activation function.
- Adam is used as a optimizer, with an initial learning rate at 0.01 or loss function based on evaluated MSE.
- Finally, the epoch number serves as hyperparameter which determines how frequently the CNN-LSTM learning algorithm gets applied to training dataset.

4. Results and Discussion

In this research study, we first performed a hyperparameter research using our customised search for neural architecture model, which was constructed based on layers of CNN and LSTM, to demonstrate the best choice of algorithm-specific hyperparameters. Overfitting is an adverse event that occurs during a training phase when the network begins to stops learning.

However, the suggested model for thermal tunnels monitoring does contain additional meteorological characteristics. In this work, the metric assessment of RMSE, MAE, and R2 was utilised to reach with little error under specific situations, making it difficult to verify tunnel detection in real-time data. The dataset is the data collected within a tunnel built by Ningbo Metro Line 3 in Ningbo, China.

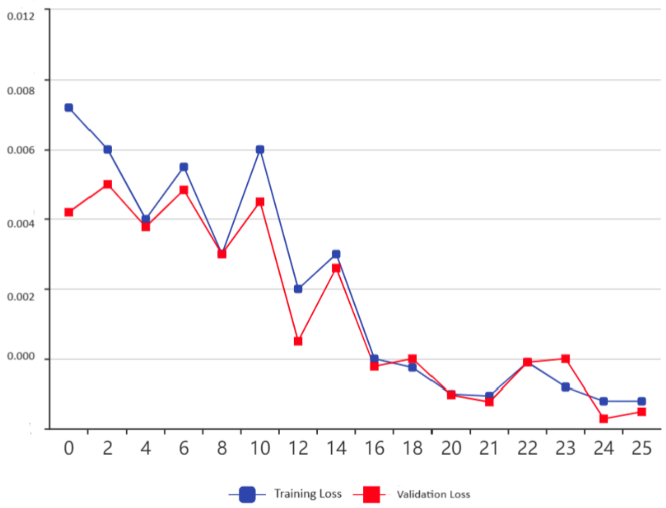

Figure 5. Training and Validation Loss

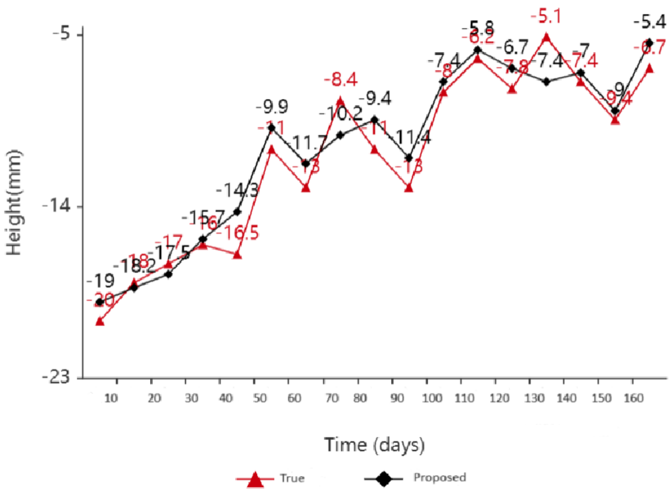

Figure 6. Real-Time Forecast

The above-shown figure is the real-time forecasting of the thermal tunnel.

$$\mathrm{MAE}(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|,$$

$$\mathrm{RMSE}(y,\hat{y}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(|y_i - \hat{y}_i|)^2},$$

$$\mathrm{MAPE}(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i}.$$

Loss functions evaluate the model's projected values against actual values to determine its effectiveness in mapping the connection between X (feature) along with Y (target). The loss, which represents the difference between expected and actual values, drives model refinement. A higher loss indicates inferior performance, requiring changes for optimal training.[10]

- y_i is the actual value
- $\hat{y_i}$ is the predicted value
- n stands for sample size

Table 1. Proposed Evaluation

Point number	**RMSE**	**MAE**	**MAPE**
204	0.19	0.07	0.53
256	.021	0.15	0.24
321	0.25	0.09	0.41
375	0.18	0.14	0.32
431	0.29	0.25	0.57
475	0.34	0.29	0.34
511	0.26	0.27	0.65

RMSE: Root mean square error

MAE: Mean Absolute Error

MAPE: Mean Absolute Percentage Error

All of the RMSE values have a value less than 0.35, MAE is below 0.3, and MAPE is lower than 6.5%, demonstrating that the suggested CNN-LSTM model can be successfully applied to the real tunnel settlement prediction issue.

5. Conclusion

This research established a hybrid deep learning approach that combines a network of convolutional neural networks with a long short-term memory network. Data Normalization and splitting of data are used during the preprocessing-preparation. The results showed that hybrid CNN as well as LSTM networks may be used to improve remote monitoring for the tunnels. The prediction subsequence's findings are concatenated to get the final prediction result. In the future, new prediction models will be investigated which perform better across all assessment measures.

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