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Application of Deep Learning Algorithms in Railway Track Degradation Modelling

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Abstract

Rail track deterioration models are integral components of rail infrastructure maintenance management systems. In particular, track geometry defects are one of the leading causes of train accidents. Also, control, management, and modification of geometric conditions are one of the most important tasks of railway maintenance management systems. Track geometry data such as profile, alignment, gauge, cross-level, and twist constantly change over time. Therefore, these features have the characteristics of time series data.

In this study, a large database from outputs of EM120, a track recording machine, was provided for the years 2009 to 2020 and for all 19 railway zones of Iranian Railways (approximately 14,000 km of railway track and 100 GB of data).
From Deep Learning techniques, CNN, LSTM, and CNN-LSTM models were selected to predict track geometry degradation. Long short-term memory (LSTM) has the advantage of analysing relationships among time-series data through its memory function, while CNN models may filter out the noise of the input data and extract more valuable features that would be more useful for the final prediction model. By integrating convolutional neural networks (CNN) with long short-term memory (LSTM), a CNN-LSTM model is considered to be more accurate and can make better point-wise predictions.

The models were built from the average segments of 100 and 200 meters. The forecasting results of proposed models were analysed and compared, and the CNN-

LSTM model with a segment length of 200 m and sequence length of 6 reported the best forecasting performance, achieving an R-squared value of 0.913.

Keywords: Railway track degradation, Deep Learning, Track geometry index, Track recording machine (EM120).

1 Introduction

Railway track deterioration occurs over time as the track is used and ages, although it can be slowed down with maintenance [1]. In order to optimize maintenance, an estimation of the track degradation is necessary [2]. Modelling and predicting track geometry degradation is a complex task based on track geometry indicators using track geometry parameters such as profile, alignment, gauge, cross-level, and twist. Track geometry parameters are measured by track geometry cars and could be used for identifying rail track irregularities, defects, and structural problems [3]. Due to the significant impact of track condition evaluation on making efficient maintenance decisions, using an appropriate track geometry indicator has always been a considerable challenge in predicting track degradation.

Track degradation modelling can be categorized into three main approaches: mechanistic, stochastic, and artificial intelligence (AI) models. Over the past decades, researchers have used different track geometry indices to represent the track condition and evaluated their efficiency in prediction models. The inability of mechanistic models to deal with uncertainty in track degradation modelling led them to statistical and AI models, which are characterized by having to handle large amounts of geometric data and input variables [4]. Statistical models are used to estimate a set of parameters from a large sample of data, where the data fit a specific distribution. However, without a mechanical background, the results may be unreliable [5]. While AI models provide an enhanced capability to solve complex problems without prior knowledge and produce more accurate estimations, their decision-making process is not transparent. In artificial intelligence fields, Machine Learning (ML) and Deep Learning (DL) seek to train a model to learn complex features from data collected and observed, but large amounts of data must be provided [6]. When using ML, features should be extracted manually and a classifier selected. In a track degradation problem, feature extraction can be using track geometry indices as the input of these models. In contrast, DL models are trained using large datasets that do not need to be manually extracted and are usually more effective as the size of the dataset increases [7].

Accordingly, DL algorithms such as Convolutional Neural Networks (CNNs), Long-Term Memory (LSTMs), and an ensemble structure of CNN-LSTM are created and analysed, using track geometry to develop railroad degradation models.

2 Methods

CNN models contain convolutional and pooling layers designed to filter the input data and extract useful knowledge to be used as inputs in a fully connected network layer, and since CNN was developed to extract features from images, the input data requires matrix structures.

LSTM networks are a subset of recurrent neural networks (RNNs) designed to solve long-term dependency problems such as exploding and vanishing gradients by storing useful information on memory cells and vanishing unnecessary information, thus providing better performance than a classic RNN. Each LSTM unit consists of a memory cell maintaining its state over time and three nonlinear gates, input, output, and forget gate, that manage data flow into and out of the cell.

Based on similar studies, the CNN–LSTM model contains two main components, first convolutional and pooling layers, which extract complex features of the input data, and then LSTM layers exploit the generated features and capture sequence pattern information due to their architecture design. Tables 1, 2, and 3 show the CNN, LSTM, and CNN-LSTM architecture and parameter settings in this study.

Parameters	Values			
Sequence length	3	4	5	6
Convolutional layer 1 filters	32	64	64	64
Convolutional layer 1 kernel size	1			
Max pooling Layer 1 kernel size	1			
Convolutional layer 2 filters	32	32	32	64
Convolutional layer 2 kernel size	1			
Max pooling Layer 1 kernel size	1			
Fully connected layer units	10			
layers activation function	relu			
Dropout layer rate	0.2	0.2	0.2	0.25
Learning Rate	0.003			
epochs	120			

Table 1: CNN model Parameters.

Parameters	Values			
Sequence length	3	4	5	6
LSTM layer 1 units	64	128	128	128
Dropout layer 1 rate	0.2	0.2	0.25	0.3
LSTM layer 2 units	64	64	64	128
Dropout layer 2 rate	0.2	0.2	0.25	0.3
Fully connected layer units	10			
LSTM layers activation function	tanh			
Learning Rate	0.001			
epochs	150			

Table 2: LSTM model Parameters.

Parameters	Values			
Sequence length	3	4	5	6
Convolutional layer filters	32	64	64	64
Convolutional layer kernel size	1			
Max pooling Layer kernel size	1			
LSTM layer 1 units	64	128	128	128
Dropout layer 1 rate	0.2	0.2	0.25	0.25
LSTM layer 2 units	64	64	64	64
Dropout layer 2 rate	0.2	0.2	0.25	0.25
Convolutional layer activation function	relu			
LSTM layers activation function	tanh			
Learning Rate	0.002			
epochs	130			

Table 3: CNN-LSTM model Parameters.

3 Results

The CNN, LSTM, and CNN-LSTM models were constructed to predict track geometry degradation, and all the deep learning models were implemented using Keras and Scikit-learn libraries. The dataset contains outputs of EM120, a track recording machine, and the necessary pre-processing was performed on it. These algorithms learned (or tested) the time series data for twelve years from 2009 to 2020 and for all 19 railway zones of Iranian Railways (approximately 14,000 km of railway track and 100 GB of data), and the sequence lengths usable for optimizing the algorithms were chosen 3, 4, 5, and 6. For each model, the dataset was randomly divided into 20% test data and 80% training data, of which 20% were considered for validation data. In order to evaluate the forecasting effect of models, mean square error (MSE) and R-square (R2) are used as the evaluation criteria of the methods. Tables 4, 5, and 6 show the results of the CNN, LSTM, and CNN-LSTM railway track degradation predictions.

Sequence length	Segment length	R^2	MSE (val_loss)	MSE (loss)	Dataset
3	100	0.752	6.73E-04	6.77E-04	1048578
	200	0.758	4.63E-04	4.72E-04	524289
4	100	0.755	4.90E-04	4.95E-04	1028578
	200	0.766	6.39E-04	6.47E-04	514289
5	100	0.781	3.62E-04	3.65E-04	1003178
	200	0.792	4.40E-04	4.41E-04	501589
6	100	0.782	3.33E-04	3.37E-04	925324
	200	0.795	3.56E-04	3.59E-04	462662

Table 4: Performance of the CNN models.

Sequence length	Segment length	R^2	MSE (val_loss)	MSE (loss)	Dataset
3	100	0.821	3.62E-04	3.89E-04	1048578
	200	0.837	3.67E-04	3.69E-04	524289
4	100	0.824	3.94E-04	3.99E-04	1028578
	200	0.845	3.98E-04	4.01E-04	514289
5	100	0.880	3.37E-04	3.41E-04	1003178
	200	0.903	3.60E-04	3.63E-04	501589
6	100	0.862	3.76E-04	3.81E-04	925324
	200	0.897	3.66E-04	3.69E-04	462662

Table 5: Performance of the LSTM models.

Sequence length	Segment length	R2	MSE (val_loss)	MSE (loss)	Dataset
3	100	0.829	3.40E-04	3.71E-04	1048578
	200	0.837	2.05E-04	2.04E-04	524289
4	100	0.826	2.27E-04	2.27E-04	1028578
	200	0.848	3.76E-04	3.83E-04	514289
5	100	0.872	2.14E-04	2.13E-04	1003178
	200	0.902	1.99E-04	2.01E-04	501589
6	100	0.898	1.70E-04	1.73E-04	925324
	200	0.913	1.93E-04	1.94E-04	462662

Table 6: Performance of the CNN-LSTM models.

4 Conclusions and Contributions

For the purpose of predicting railway track degradation, CNN, LSTM, and CNN-LSTM algorithms were implemented using track geometry data and from the average segments of 100 and 200 meters. In all models, the 200 m segments provided better performance than the 100 m segments, which is probably due to the fact that the smaller segments are more sensitive to degradation and have a greater rate of change. Generally, in the case of the window size of a time series in a prediction problem, a smaller window size requires a simpler architecture, which results in less overfitting. In addition, using less historical data is more desirable. According to the results, models performance generally improved by increasing the length or size of the time series window. In the CNN and CNN-LSTM algorithms, models with a sequence length of 6 reported the best forecasting performance, and with a slight difference, LSTM models with a sequence length of 5 had a better performance. This difference could be caused by the increased probability of changes due to maintenance activities on the railway track.

Respectively, CNN-LSTM, CNN, and LSTM models performed better and achieved a better prediction, while in terms of learning time, the CNN models were much faster than CNN-LSTM and LSTM models. It is likely that the combination of the feature extraction property of CNNs with the ability to analyse the interdependence of time series data in LSTM models resulted in an improvement in performance for CNN-LSTM models.

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