International Conference on Formal Methods
and Foundations of Artificial Intelligence
Eszterházy Károly Catholic University
Eger, Hungary, June 5–7, 2025

An LSTM Approach for Fault Prediction*

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Abstract

The prevention and prediction of industrial equipment failures are critical tasks in manufacturing environments. Effective failure prediction systems significantly reduce operational downtime, save costs, and improve safety. This paper presents an examination of Long Short-Term Memory (LSTM) [5] neural networks applied specifically to industrial fault prediction [7]through sequential data analysis.

LSTM networks, a special class of recurrent neural networks (RNNs) [8], have been widely recognized for their exceptional capabilities in processing sequential data [3]. Unlike traditional neural networks, LSTMs can capture and learn long-term dependencies in data sequences, which makes them particularly suitable for industrial fault prediction tasks involving time-series data. The theoretical foundation of LSTM, including its capability to maintain memory across multiple timesteps through specialized gating mechanisms (input gate, output gate, and forget gate), enables effective management of information flow and addresses the critical issues of vanishing and exploding gradients encountered in standard RNNs.

The document outlines the development process of an LSTM-based prediction model, beginning with data compilation and preparation. Appropriate datasets must include comprehensive operational parameters and labeled fault occurrences, structured chronologically to accurately reflect pre- and post-failure states. Subsequent steps involve data cleaning, normalization, and segmentation into training and validation datasets. Proper sequencing is critical [4], [2], necessitating precise construction of temporal data windows and clear separation between input parameters and target prediction outputs. The construction of the LSTM predictive model assumes the creation of an architecture that uses multiple LSTM layers capable of modeling complex temporal dependencies inherent in industrial datasets.

*Nemzeti Kutatási Fejlesztési és Innovációs Hivatal 2020-1.1.2-PIACI-KFI-2020-00147 pályázati támogatásával valósult meg.

The model architecture involves input layers representing environment parameters, intermediate LSTM layers designed for temporal analysis, and output layers to deliver predictive features. Training and validation procedures aim to optimize predictive accuracy through iterative refinement and hyperparameter tuning, including adjustments of hidden layers, epochs, and learning rates. Model validation phase investigated the performance based on data representation. Initially, binary classification model (see Figure 1) (fault vs. no fault) showed limitations in predictive accuracy due to overfitting, especially with smaller datasets. Recognizing this, the binary classification approach was subsequently transformed into a Remaining Useful Life (RUL) prediction model using a linear approximation. This shift significantly improved the accuracy and reliability of predictions, highlighting the adaptability of LSTM models in handling different prediction paradigms. In conclusion, the implementation of LSTM neural networks for industrial fault prediction underscores their valuable role in predictive maintenance strategies. The capability of LSTM models to effectively predict equipment failures through sophisticated sequence analysis positions them as powerful tools in reducing downtime and enhancing operational efficiency in industrial environments. The study emphasizes both the strengths and limitations [1] of LSTM networks. While their advanced memory handling and temporal sequence modeling capabilities represent significant advantages over other predictive models, challenges such as overfitting and the "constant error carousel" [5] phenomenon require careful management. These issues can be eleminated through refined model design, hyperparameter adjustments, and data preprocessing strategies. The research also acknowledges alternative AI methods structures like AdaBoost [6], which may provide better results for specific sequence-dependent applications.

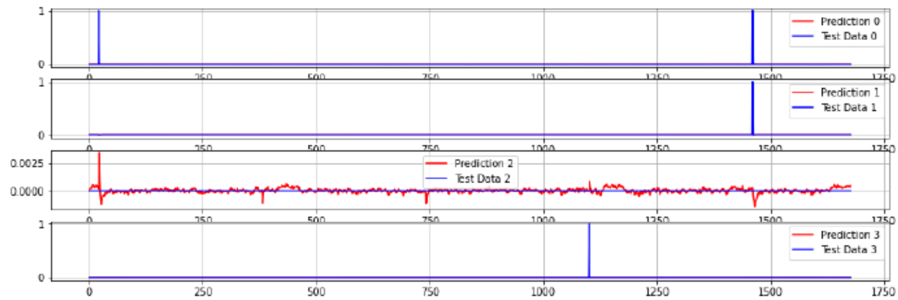

Figure 1. Binary LSTM classification

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