ABSTRACT

This project presents a deep learning approach for predicting train delays by integrating operational and environmental factors that influence railway performance. The proposed system evaluates four models — Deep Neural Network (DNN), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Bidirectional LSTM (BiLSTM). Each model is trained on a structured dataset that includes attributes such as distance between stations, weather conditions, day of the week, time slot, train type, historical delays, and route congestion levels. Data preprocessing involves cleaning, encoding categorical variables, and normalization to ensure model accuracy. Among all models, BiLSTM performs the best, achieving superior results across evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), and Symmetric Mean Absolute Percentage Error (sMAPE). This demonstrates BiLSTM's ability to capture both forward and backward temporal dependencies in sequential data, making it highly effective for real-time train delay forecasting. The model is optimized using the Adam optimizer and trained over multiple epochs to ensure stability and precision. Extensive experiments show that the BiLSTM model consistently outperforms others with an R^2 of 96.17%, confirming its robustness in handling dynamic railway delay patterns. Furthermore, the system's modular architecture supports real-time prediction, enabling integration into smart transport systems for proactive scheduling and passenger information. Future work can extend this framework using transformer-based architectures or real-time sensor data for even more accurate delay management across large-scale railway networks.