INTISARI

IMPLEMENTASI METODE PRINCIPAL COMPONENT ANALYSIS-LONG SHORT TERM MEMORY PADA PERAMALAN PERMINTAAN INDUSTRI RITEL

Peramalan permintaan merupakan aspek krusial dalam pengambilan keputusan di industri ritel, khususnya dalam manajemen persediaan dan perencanaan operasional. Penelitian ini mengkaji pengaruh penerapan Principal Component Analysis (PCA) terhadap performa model Long Short-Term Memory (LSTM) dalam peramalan permintaan industri ritel. Dataset transaksi ritel multivariat diproses melalui tahapan pra-pemrosesan, standardisasi, dan reduksi dimensi dengan PCA (threshold 90%), sebelum digunakan untuk pelatihan model LSTM, GRU, dan RNN. Evaluasi dilakukan menggunakan metrik RMSE, MAE, dan waktu pelatihan pada tiga rasio data latih, validasi, dan uji (60:20:20, 70:20:10, 80:10:10). Hasil menunjukkan bahwa PCA-LSTM dengan konfigurasi optimal mampu menurunkan RMSE sebesar 8,3% (dari 6.258 menjadi 5.736) dan mempercepat waktu pelatihan sebesar 27,9% (dari 72,70 detik menjadi 52,42 detik), menjadikannya model paling akurat dalam studi ini. Namun, efektivitas PCA tidak berdapmak sama seperti pada LSTM. Pada model RNN, PCA menyebabkan penurunan akurasi (RMSE naik 19%, MAE naik 44%), yang mungkin terjadi akibat hilangnya informasi penting dari fitur asli yang tidak terwakili dalam komponen utama. Temuan ini menegaskan bahwa efektivitas PCA sangat bergantung pada arsitektur model dan sensitivitasnya terhadap detail input.

Kata kunci: *Demand Forecasting*, *deep learning*, reduksi dimensi, Long-Short Term Memory (LSTM), Principal Component Analysis (PCA)

ABSTRACT

IMPLEMENTATION OF PRINCIPAL COMPONENT ANALYSIS-LONG SHORT TERM MEMORY METHOD IN RETAIL INDUSTRY DEMAND FORECASTING

Demand forecasting is a crucial aspect in decision making in the retail industry, especially in inventory management and operational planning. This study examines the effect of applying Principal Component Analysis (PCA) on the performance of the Long Short-Term Memory (LSTM) model in demand forecasting in the retail industry. The multivariate retail transaction dataset was processed through pre-processing, standardization, and dimensionality reduction stages with PCA (threshold 90%), before being used for training LSTM, GRU, and RNN models. Evaluation was carried out using RMSE, MAE, and training time metrics on three ratios of training, validation, and testing data (60:20:20, 70:20:10, 80:10:10). The results showed that PCA-LSTM with the optimal configuration was able to reduce RMSE by 8.3% (from 6,258 to 5,736) and speed up training time by 27.9% (from 72.70 seconds to 52.42 seconds), making it the most accurate model in this study. However, the effectiveness of PCA is not uniform. In the RNN model, PCA causes a decrease in accuracy (RMSE increases by 19%, MAE increases by 44%), possibly due to the loss of important information from the original features that are not represented in the principal components. This finding confirms that the effectiveness of PCA is highly dependent on the model architecture and its sensitivity to input details.

Keywords: Demand Forecasting, deep learning, dimensionality reduction, Long-Short Term Memory (LSTM), Principal Component Analysis (PCA)