Time Series Forecasting Analysis

Models Developed and MAE Evaluation

Model 1: Baseline Model

MAE: 2.62

Model 2: Basic machine learning model

MAE: 2.64

Model 3: Convolutional Neural Network (CNN)

MAE: 3.04

Model 4: LSTM

MAE: 2.59

Model 5: LSTM (dropout regularization)

MAE: 2.58

Model 6: LSTM (16 units)

MAE: 2.61

Model 7: LSTM (8 units)

Method: Gated Recurrent Unit network.

MAE: 2.54

Model 8: LSTM (dropout regularization 8 units)

MAE: 2.56

Model 9: LSTM (Bidirectional)

MAE: 2.56

Model 10: Hybrid CNN + LSTM

Method: Combination of CNN and LSTM.

MAE: 3.79

Model 11:Simple GRU (Gated Recurrent Unit)

MAE: 2.51

Key Findings

LSTM and GRU Models: Both effectively captured temporal dependencies, with the best Model 7, LSTM (8 units) achieving the lowest MAE of 2.54.

Hybrid Models: The combination of CNN and LSTM (Model 10) did not perform well, likely due to the challenges in maintaining sequence integrity.

Model Enhancements: Fine-tuning hyperparameters and configurations of LSTM significantly improved performance.

MAE Evaluation

The Bar chart displays the MAE for each model, highlighting the comparative performance. The best-performing model was the Simple GRU (Gated Recurrent Unit) with an MAE of 2.51, followed closely by various configurations of LSTM models.

Conclusion

For accurate time series forecasting, advanced recurrent neural network architectures like LSTM and GRU are recommended due to their ability to handle long-term dependencies and avoid issues such as the vanishing gradient problem. Optimizing model configurations and hyperparameters is crucial for achieving the best performance. Hybrid models, although promising, need careful tuning to maintain the sequence data's integrity.