

**PREDIKSI HARGA MINYAK MENTAH *WEST TEXAS*  
*INTERMEDIATE* (WTI) MENGGUNAKAN METODE *LONG*  
*SHORT-TERM MEMORY* (LSTM) DENGAN INTEGRASI FAKTOR  
*SUPPLY-DEMAND*, INDEKS DOLAR, DAN RISIKO GEOPOLITIK**

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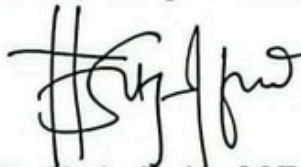
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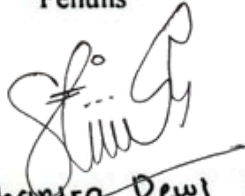
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## ABSTRAK

### **PREDIKSI HARGA MINYAK MENTAH *WEST TEXAS INTERMEDIATE* (WTI) MENGGUNAKAN METODE *LONG SHORT-TERM MEMORY* (LSTM) DENGAN INTEGRASI FAKTOR *SUPPLY-DEMAND*, INDEKS DOLAR, DAN RISIKO GEOPOLITIK**

Harga minyak mentah *West Texas Intermediate* (WTI) merupakan salah satu indikator penting dalam pasar energi global yang pergerakannya dipengaruhi oleh keseimbangan *supply-demand*, indeks dolar, dan risiko geopolitik. Fluktuasi harga yang tinggi menyebabkan perlunya metode prediksi yang mampu menangkap pola nonlinier dan ketergantungan jangka panjang pada data deret waktu. Penelitian ini bertujuan untuk memprediksi harga minyak mentah WTI menggunakan metode *Long Short-Term Memory* (LSTM) dengan mengintegrasikan faktor *supply-demand*, *Indeks Dolar* (DXY), dan *Geopolitical Risk Index* (GPR). Data yang digunakan merupakan data harian periode 1 September 2021 hingga 30 September 2025. Tahapan penelitian meliputi interpolasi linear untuk mengatasi data yang hilang, normalisasi *Min-Max*, pembentukan *windowing*, pelatihan model dengan berbagai kombinasi parameter, serta evaluasi menggunakan RMSE dan MAPE. Hasil penelitian menunjukkan bahwa model LSTM mampu menghasilkan prediksi harga minyak mentah WTI dengan tingkat akurasi yang tinggi. Model terbaik memperoleh nilai MAPE sebesar 2,296% dan RMSE sebesar 2,1915. Analisis *feature importance* menunjukkan bahwa variabel impor minyak mentah memberikan kontribusi paling dominan terhadap perubahan harga WTI dibandingkan variabel lainnya. Hasil penelitian menunjukkan bahwa integrasi faktor eksternal dapat meningkatkan kemampuan model dalam memprediksi harga minyak mentah WTI secara akurat.

**Kata kunci:** Minyak Mentah WTI, *Supply-Demand*, Indeks Dolar, Risiko Geopolitik, LSTM

## ABSTRACT

### WEST TEXAS INTERMEDIATE (WTI) CRUDE OIL PRICE PREDICTION USING THE LONG SHORT-TERM MEMORY (LSTM) METHOD WITH INTEGRATION OF SUPPLY-DEMAND FACTOR, DOLLAR INDEX, AND GEOPOLITICAL RISK

The price of *West Texas Intermediate* (WTI) crude oil is a key indicator in the global energy market, with its movements influenced by the *supply-demand* balance, dollar index, and geopolitical risks. High price volatility necessitates forecasting methods capable of capturing nonlinear patterns and long-term dependencies in time-series data. This study aims to predict WTI crude oil prices using the *Long Short-Term Memory* (LSTM) method by integrating *supply-demand* factors, the *U.S. Dollar Index* (DXY), and the *Geopolitical Risk Index* (GPR). The data used consists of daily data from September 1, 2021, to September 30, 2025. The research stages include linear interpolation to address missing data, *Min-Max* normalization, *windowing*, model training with various parameter combinations, and evaluation using RMSE and MAPE. The results show that the LSTM model is capable of generating WTI crude oil price predictions with a high level of accuracy. The best model achieved a MAPE of 2.296% and an RMSE of 2.1915. Feature importance analysis indicates that the crude oil import variable contributes most significantly to changes in WTI prices compared to other variables. The results suggest that incorporating external factors can enhance the model's ability to predict

**Keywords:** *WTI Crude Oil, Supply-Demand, Dollar Index, Geopolitical Risk, LSTM*

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