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EXPLORING THE EFFECTIVE TECHNICAL INDICATORS OF LSTM FOR WTI PRICE IN DIFFERENT REGIMES

(*Meneroka Petunjuk Teknikal Berkesan LSTM untuk Harga WTI dalam Rejim Berbeza*)

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ABSTRACT

This study aims to explore the effectiveness of technical indicators in predicting WTI crude oil prices and investigate their applicability in different oil price regimes. By collecting monthly WTI data, we analyzed the closing prices using the Markov switching regression (MS-Regression) modeling approach. The study reveals that the market conditions can be divided into two distinct periods: low oil price regime and high oil price regime. For each of these periods, we employed LSTM regression models with the 30 least correlated technical indicators as features to predict the closing prices for the subsequent period. The MSE, RMSE, MAE, and MAPE were calculated for the test sets of both regimes. For Regime 1, the results were 43.409, 6.588, 4.745, and 10.299%, respectively. For Regime 2, the corresponding values were 120.872, 10.994, 8.521, and 9.371%, respectively. The results demonstrate that the models perform more accurately in predicting price fluctuations during the high oil price regime. Furthermore, through feature importance analysis, we identified the effectiveness of `SMA_20`, `MIDPOINT_14`, and `BBANDS_middle_20_2` indicators in both low and high oil price regimes. Additionally, `BBANDS_upper_20_2` and `CCI_14` exhibit better predictive capabilities during the low oil price regime, while `NATR_14` and `RSI_14` prove more effective during the high oil price regime. These findings contribute to a better understanding of the role of technical indicators in predicting WTI crude oil prices in different oil price regimes.

Keywords: WTI; MS-Regression; technical indicators; LSTM; feature importance

ABSTRAK

Kajian ini bertujuan untuk meneroka keberkesanan penunjuk teknikal dalam meramalkan harga minyak mentah WTI dan menyiasat kebolehgunaannya dalam rejim harga minyak yang berbeza. Dengan mengumpul data WTI bulanan, kami menganalisis harga penutup menggunakan pendekatan pemodelan regresi pertukaran Markov (MS-Regression). Kajian ini mendedahkan bahawa keadaan pasaran boleh dibahagikan kepada dua tempoh berbeza: rejim harga minyak rendah dan rejim harga minyak tinggi. Bagi setiap tempoh ini, kami menggunakan model regresi LSTM dengan 30 petunjuk teknikal yang paling kurang berkorelasi sebagai ciri untuk meramalkan harga penutup untuk tempoh berikutnya. MSE, RMSE, MAE, dan MAPE telah dikira untuk set ujian kedua-dua rejim. Bagi Rejim 1, keputusannya adalah 43.409, 6.588, 4.745, dan 10.299%, masing-masing. Manakala bagi Rejim 2, nilai yang sepadan ialah 120.872, 10.994, 8.521, dan 9.371%, masing-masing. Keputusan menunjukkan bahawa model berprestasi lebih tepat dalam meramal turun naik harga semasa rejim pada harga minyak yang tinggi. Tambahan pula, melalui analisis kepentingan ciri, kami mengenal pasti keberkesanan penunjuk `SMA_20`, `MIDPOINT_14` dan `BBANDS_upper_20_2` dalam kedua-dua rejim harga minyak rendah dan tinggi. Selain itu, `BBANDS_upper_20_2` dan `CCI_14` mempamerkan keupayaan ramalan yang lebih baik semasa rejim harga minyak rendah, manakala `NATR_14` dan `RSI_14` terbukti lebih berkesan semasa rejim harga minyak yang tinggi. Penemuan ini menyumbang kepada pemahaman yang lebih baik tentang peranan penunjuk teknikal dalam meramalkan harga minyak mentah WTI dalam rejim harga minyak yang berbeza.

Kata kunci: WTI; Regresi MS; penunjuk teknikal; LSTM; kepentingan ciri

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