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STOCK MARKET PREDICTION WITH COMPLEXITY INDICATORS AND DEEP LEARNING APPROACHES

Financial markets are complex, nonlinear, and non-stationary systems. This study investigates whether indicators from complexity science can improve S&P 500 forecasting when combined with deep learning models. The relevance of this problem is strengthened by the difficulty of detecting hidden structural changes that often precede crises or regime shifts. Traditional metrics based mainly on returns and volatility may fail to reveal early warning signals. In contrast, complexity measures - including multifractal indicators, visibility-graph metrics, and recurrence statistics - can capture subtle changes in price dynamics before they are fully reflected in market prices [1-5].

We consider three classes of complexity indicators. Multifractal analysis quantifies the scaling heterogeneity of financial time series and reflects how fluctuation patterns vary across time scales [1; 2]. Network-based indicators use the visibility graph method, which converts a time series into a graph while preserving important structural features of the series [3; 4]. Graph metrics, such as spectral radius, graph energy, connectivity, and graph complexity, then describe the underlying market topology. Recurrence quantification analysis (RQA) examines how often the market state returns to previously visited regions of phase space and yields measures such as recurrence rate, determinism, and entropy [5]. These complementary methods provide several perspectives on market complexity.

To track indicator dynamics, each metric was computed in rolling windows of 100, 250, and 500 trading days. Shorter windows capture local and reactive changes, whereas longer windows reveal broader regime shifts. This sliding-window approach avoids treating the entire market history as a single stationary sample and allows us to observe how complexity evolves over time. It is motivated by the assumption that crises can develop gradually in the market's internal structure before they become visible as sharp price movements.

Two forecasting tasks were formulated. First, a binary classification task predicts whether the future S&P 500 return will be positive or negative. Second, a regression task predicts the future standardized return value. Forecast horizons of 7, 14, and 21 days ahead were used to assess performance over different time scales. The data pipeline merged the S&P 500 price series with all calculated complexity indicators. After converting inputs to numerical form, we constructed target variables for each horizon. The data were split chronologically into training and test sets, with a temporal gap to reduce the risk of leakage.

Key preprocessing included rolling standardization. Each feature and price series was standardized using 50-day rolling statistics shifted forward in time, ensuring that no future

information was used in scaling. This procedure avoids look-ahead bias while stabilizing features that may otherwise have low variance during calm market periods. Feature selection was then performed using mutual information: the most informative indicators were selected separately for each task and horizon. The retained feature sets often included the S&P 500 price series and several network-based metrics, such as spectral moments, graph complexity, and natural connectivity. This result suggests that market topology contains useful predictive information. Mutual information measures statistical dependence between variables; therefore, higher mutual information with the target implies stronger relevance for forecasting.

The selected features were arranged as three-dimensional tensors for deep learning. Each training sample was represented by a window of 30 past observations of each selected indicator, organized as channels by time steps. For example, with 11 channels and a 30-day history, each sample has a dimension of 11 x 30. Several deep neural architectures were tested, including recurrent networks (LSTM and GRU) and convolutional networks (simple CNNs, multiscale CNNs with attention, and fully connected CNNs). These choices are consistent with recent literature on financial and general time-series forecasting, where LSTM, GRU, CNN, attention-based, and transformer architectures are widely used for sequential prediction [6-9]. Models were trained chronologically, without shuffling, and hyperparameters were tuned using ROC-AUC for classification and mean absolute error for regression.

The results show that including complexity indicators leads to reasonable forecasting accuracy, especially for market direction. Classification performance improved at longer horizons. At the 7-day horizon, the best model, a multiscale deep CNN, achieved an AUC of approximately 0.63 and an accuracy of about 59%. At the 14-day horizon, accuracy rose to about 63%. At the 21-day horizon, the best accuracy reached approximately 66%, with an AUC of about 0.71. These results suggest that slow-moving structural features of the market are more informative for medium-term trend prediction than for short-term fluctuations. Regression results were more modest: test-set R-squared values remained low, reflecting the high volatility and noise of daily returns. Nevertheless, the predicted series captured broad directional tendencies in the true returns, even though point estimates remained noisy.

These findings support the hypothesis that complexity indicators provide useful information about future market dynamics. Network and multifractal measures often ranked among the most informative predictors, indicating that the market's topological and scaling structure encodes forecasting signals. The stronger results at longer horizons imply that complexity indicators are more effective for anticipating medium-term trend direction than for estimating exact daily returns. This is consistent with evidence that fractal and recurrence patterns can change during periods of stress and may help reveal transitions in market dynamics [1; 3-5]. Deep learning models, including LSTM, GRU, and CNN architectures, were able to exploit these signals, in line with survey evidence on their suitability for financial time-series prediction [6-8].

In conclusion, this work demonstrates that combining complex-systems analysis with deep learning can improve stock market forecasting. Complexity indicators based on multifractality, network topology, and recurrence complement traditional financial metrics by revealing hidden market structure. Their practical value lies in earlier detection of regime shifts and improved trend prediction. Future research should extend the framework by adding entropy- and irreversibility-based indicators, exploring additional neural architectures and hyperparameters, and applying the approach to other markets and assets, including sector indices, commodities, and cryptocurrencies. Separate analysis of major crises, such as the 2008 global financial crisis and the COVID-19 pandemic, would also clarify how well these indicators anticipate real-world shocks.

References

1. Zhang, S., & Fang, W. (2021). Multifractal behaviors of stock indices and their ability to improve forecasting in a volatility clustering period. *Entropy*, 23(8), 1018. <https://doi.org/10.3390/e23081018>.

2. Tiwari, A. K., Aye, G. C., & Gupta, R. (2019). Stock market efficiency analysis using long spans of data: A multifractal detrended fluctuation approach. *Finance Research Letters*, 28, 398-411. <https://doi.org/10.1016/j.frl.2018.06.012>.
3. Vamvakaris, M. D., Pantelous, A. A., & Zuev, K. M. (2018). Time series analysis of S&P 500 index: A horizontal visibility graph approach. *Physica A: Statistical Mechanics and its Applications*, 497, 41-51. <https://doi.org/10.1016/j.physa.2018.01.010>.
4. Soloviev, V., Solovieva, V., & Tuliakova, A. (2019). Visibility graphs and precursors of stock crashes. *Neuro-Fuzzy Modeling Techniques in Economics*, 8, 3-29. <https://doi.org/10.33111/nfmte.2019.003>.
5. Krishnadas, M., Harikrishnan, K. P., & Ambika, G. (2022). Recurrence measures and transitions in stock market dynamics. *Physica A: Statistical Mechanics and its Applications*, 608, 128240. <https://doi.org/10.1016/j.physa.2022.128240>.
6. Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research*, 270(2), 654-669. <https://doi.org/10.1016/j.ejor.2017.11.054>.
7. Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review: 2005-2019. *Applied Soft Computing*, 90, 106181. <https://doi.org/10.1016/j.asoc.2020.106181>.
8. Lim, B., & Zohren, S. (2021). Time-series forecasting with deep learning: A survey. *Philosophical Transactions of the Royal Society A*, 379(2194), 20200209. <https://doi.org/10.1098/rsta.2020.0209>.
9. Lim, B., Arik, S. O., Loeff, N., & Pfister, T. (2021). Temporal Fusion Transformers for interpretable multi-horizon time series forecasting. *International Journal of Forecasting*, 37(4), 1748-1764. <https://doi.org/10.1016/j.ijforecast.2021.03.012>.