Review of: "Machine Learning Methods in Algorithmic Trading: An Experimental Evaluation of Supervised Learning Techniques for Stock Price"

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Potential competing interests: No potential competing interests to declare.

Strengths:

Comprehensive Evaluation: The paper thoroughly evaluates a range of machine learning models (NBeats, NHits, RNN, LSTM, and transformers) for stock and currency price prediction. This extensive comparative analysis is a significant strength, as it provides valuable insights into model performance.

Clear Methodology: The research methodology, including data collection, preprocessing, partitioning, and evaluation metrics, is well-defined and systematic. This clarity makes it easy to follow the research process.

Practical Application: The implementation of the TradingHelper bot is a notable strength, as it demonstrates the real-world applicability of the research findings. This application has the potential to benefit traders and investors.

Transparent Discussion of Limitations: The paper acknowledges potential limitations, such as data quality issues and model interpretability challenges. This transparency enhances the credibility of the research.

Future Directions: The paper outlines promising future directions for research, including the development of hybrid models and the integration of external indicators. This forward-looking approach showcases the potential for continued improvement.

Weaknesses:

Lack of Qualitative Analysis: While the paper extensively discusses quantitative evaluation metrics (MSE, MAE, and RMSE), it lacks qualitative analysis of why certain models performed better than others. Adding qualitative insights into model behavior could enhance the paper's depth.

Explanation of Hyperparameters: The paper briefly mentions hyperparameters for model training but doesn't delve into how these were selected or their impact on results. A more detailed discussion of hyperparameter tuning would provide better context.

Limited Data Description: The paper mentions collecting historical data but lacks details about the sources, frequency, or any potential data preprocessing challenges. Providing a more comprehensive description of the data sources and potential data issues would enhance transparency.

Interpretability Discussion: The paper mentions model interpretability as a potential limitation but does not explore this aspect further. Discussing methods or techniques for making these complex models more interpretable would be beneficial.

Further Discussion of Trading Bot: While the TradingHelper bot is an interesting addition, more details about its implementation, how it integrates with models, and its performance in real trading scenarios would add depth to this aspect of the research.

Suggestions for Improvement:

Qualitative Analysis: Include qualitative analysis or visualizations to help readers understand why certain models outperform others. This could involve examining how each model captures different patterns in the data.

Hyperparameter Tuning: Provide a more detailed discussion of the hyperparameter tuning process, including the rationale behind hyperparameter choices and their impact on model performance.

Data Description: Offer a more comprehensive description of the data used, including data sources, frequency, any data preprocessing steps, and potential challenges in data collection.

Interpretability Solutions: Explore methods or techniques for making the models more interpretable. This could include discussing techniques like SHAP values or feature importance analysis.

Trading Bot Performance: Provide more information about the TradingHelper bot's implementation, its integration with models, and its performance in real trading scenarios. This would make the practical application aspect more robust.

Incorporating these suggestions could enhance the paper's overall quality and make it more valuable to readers and researchers in the fields of financial forecasting and machine learning.