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Research Paper

Comparing the Performance of Algorithmic Trading Systems Based on Machine Learning In The Cryptocurrency Market[1]

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INTRODUCTION

Price prediction in financial markets is crucial for traders and investors, as it can significantly impact their success (Jianek et al., 2019). Among financial markets, the cryptocurrency market has garnered attention due to its remarkable growth from 2015 to 2017 and again from 2019 to 2021. Bitcoin, introduced by Nakamoto in 2008, stands as the most prominent cryptocurrency, leveraging blockchain technology and cryptography for secure peer-to-peer financial transactions (Nakamoto, 2008). Given its significance, predicting Bitcoin prices can serve as a barometer for the cryptocurrency market, given the high correlation of other currencies (altcoins) with Bitcoin.

This research endeavors to forecast Bitcoin price ceilings and floors using supervised machine learning models. To address the research objectives, the following questions were formulated:

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1. How does the performance of intelligent trading systems based on random forest prediction models, long and short term memory learning, recurrent neural networks, and collective learning compare to real data and the buy-and-hold strategy?
2. What is the precision and accuracy of collective machine learning in predicting Bitcoin price ceilings and floors?
3. Does collective machine learning achieve higher precision and accuracy in predicting Bitcoin price ceilings and floors compared to sub-algorithms?

RESEARCH METHODOLOTY

Candle price data (OHLCV) for Bitcoin in the 1-hour time frame were chosen as representative cryptocurrency market data. The Historic-Crypto Python module, extracting data from the CoinBase Pro exchange API, facilitated data collection. Given the cryptocurrency market's 4-year cyclical behavior due to mining reward halving, the analysis period (T) was selected from Bitcoin data available since 2010 for the years 2018 to 2022.

The dataset was divided as follows: 70% for training data, 20% for validation data, and the remaining 10% for test data. Implementation was carried out using the Python programming language and its various modules. The Google Colab platform, benefiting from GPU sharing, and libraries such as numpy, Pandas, ta, tensorflow, sklearn, and Scipy were utilized.

The implementation steps were as follows:

Step 1: Prediction of Bitcoin ceiling and floor data as target variables using random forest models, long short-term memory (LSTM), and recurrent neural networks (RNN) with feature variables. The output included ceiling and floor predictions from each model, along with their respective scores.

Step 2: Presentation of the output from Step 1, including ceilings and floors as target variables, along with feature variables, to XGBoost and LightGBM models for further learning.

Step 3: Recording of results obtained from Step 2 using the collective learning algorithm of voting, iteratively refining predictions until final prediction results were obtained and compared with real data.

Step 4: Utilization of results from RNN, LSTM, and random forest prediction models, along with proposed collective learning, for buy and sell signals in the cryptocurrency market. Performance of the trading strategy based on these signals was compared with a trading system based on real Bitcoin ceiling and floor data.

RESULTS AND DISCUSSION

1. The results presented in the model execution section affirm the study's hypothesis regarding the enhanced prediction accuracy of the proposed model compared to each of the sub-algorithms. The collective learning module demonstrated superior performance over any individual sub-algorithm across various indicators including accuracy, correctness, coverage, and F1 score.
2. Consequently, in addressing the research questions:
3. The intelligent algorithmic trading system based on collective learning proposed in this research achieved a yield closer to that of the trading system based on real ceiling and floor data. Furthermore, its risk (investment loss index) was lower compared to the system based on real data and outperformed other systems.
4. The collective learning model exhibited an accuracy of 81.31% for predicting the ceiling condition and 82% for predicting the floor condition of Bitcoin prices.
5. The collective learning model demonstrated higher accuracy and precision compared to all sub-algorithms, as evidenced by indicators such as accuracy, correctness, coverage, and F1 score.

CONCLUSION

While the model proposed in this research represents an innovative aspect, the study encountered several limitations. The stopping condition, coupled with the lower time frame, necessitates hardware with relatively high specifications due to computational complexity. Similarly, processing multiple assets simultaneously also demands robust computational resources. Additionally, the slight variation in Bitcoin prices across different exchanges may impact model performance and output.

Hence, future studies are advised to explore multi-asset data integration concurrently. Furthermore, incorporating alternative indicators such as ZigZag to detect ceilings and floors, and comparing them with the current model utilizing the AO indicator, could provide valuable insights. Additionally, future research could consider incorporating fundamental and perceptual market variables as feature variables to enhance forecasting accuracy. Moreover, comparing different models and assessing the impact of adding these variables could yield valuable findings for future research endeavors.

Keywords: Algorithmic Trading, Price Ceiling and Floor Prediction, Machine Learning, XGBoost, LightGBM.

JEL Classification: F17, F19, G17, B17, C53.