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Trading Software Using Blockchain Technology

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***Abstract*:**Traders and speculators are paying more attention to Bitcoin as it becomes a more well recognized asset globally. Due to its extreme volatility, the cryptocurrency market has drawn interest from those looking to take advantage of large price swings for possible financial benefits. This study explores algorithmic trading tactics in the Bitcoin market, focusing on daily price fluctuations using directional categorization. Expanding on previous research, our method improves machine learning models' predictive power by integrating a wide range of characteristics, including as external variables and internal Bitcoin network metrics. In order to verify the performance among our models, we empirically assess them with gathered real-world trade data in the initial three months of 2023. When a predictor that is binary is used, our models show an average by the conclusion of the triennial trading cycle, 86% revenue, which is consistent with the results of conventional buy-and-hold tactics. Interestingly, our models incorporate a risk-perception index that is derived from prediction assurance of the models, which goes beyond traditional tactics. Performance gains from this combination outpace the returns from a straightforward buy-and-hold strategy by a factor of 12.5. These results highlight how machine learning models have a great deal of potential for profitably mining the volatile Bitcoin market. The efficacy noted in practical trading situations stimulates additional investigation and study in the area of trading algorithms tactics customized in relation to Bitcoin network.

Keywords: Blockchain; Algorithmic Trading; Bitcoin; Machine Learning; Time Series Classification; Support Vector Machine

1. Introduction

Retail investor has come to appreciate cryptocurrencies because of their high volatility and potential for substantial financial gain. Capitalizing on its high speed and bandwidth capabilities, algorithmic trading has emerged as a key participant in this arena, in contrast to human day traders who frequently struggle to foresee market swings [Chague et al., 2020]. Among all cryptocurrencies that available regarding exchanges, Bitcoin (Nakamoto, 2008) is the most popular valued and well-known, accounting for about 43% of the market. Although trading opportunities cannot be guaranteed just by intrinsic value, Bitcoin's market liquidity, with 7% of its entire value moved daily, offers an ideal environment for algorithmic trading [CoinMarketCap, 2021].

Trading algorithms use their knowledge of market dynamics and present circumstances to mimic human traders estimate the underlying asset's future price. The goal of this research is to apply machine learning algorithms to categorize the direction of Bitcoin price movements the next day. According to earlier research (Sebastião and Godinho, 2021; Mudassir et al., 2020)), choosing a one-day prediction period works well. Moreover, daily data measurements are essential since the features they offer have a big impact on how well the algorithms categorize daily price changes.

Building upon the work of Mudassir et al. [2020], our method includes attributes that describe the Bitcoin network together with a variety of technical indicators that are generated from these qualities. Although prior research [Ji et al., 2019, Huang et al., 2019, Balcilar et al., 2017] has demonstrated the effectiveness of internal Bitcoin network properties, it is important to recognize their limits in capturing other market characteristics that are important to investors and speculators. These consist of data from social media, the stock market, commodities, currency exchange, and the economy. Our study offers a more thorough method to feature expansion, whereas previous publications [In 2018, Mai and colleagues Chen et al., 2020; Lyócsa et al., 2020 2019's Mallqui and

Fernandes 2021's Jaquart et al.] have only partially addressed this research gap.

The following is a brief summary of the important contributions made by this paper:

• As far as we are aware, we all set a new standard in this case, machine learning field by presenting what we believe to be the most reliable an algorithm for exchanging bitcoins published thus far. Our main goal is to examine and validate the models' performance as stated in earlier researches, bringing to light concerns related to overfitting—a prevalent issue in published data science research. We present an algorithmic strategy for trading Bitcoin that combines several elements. Notably, previous research have not fully utilized these aspects when taken into account as a whole. Crucially, there is no discernible difference in the performance of the model when these features are used in their unaltered state.

• We empirically test our built model on previously unseen data acquired in 2021 to show its effectiveness in real-world trading. This method offers a consistent statistic that goes beyond traditional metrics to evaluate model performance.

• We naturally parameterize trading risk by using the probabilistic outputs of the classifiers, giving traders flexibility in defining their risk appetite. This indicates that traders who are more willing to take risks typically make more money.

The following is the format of the paper's succeeding sections: We investigate the reproducibility of a well-known article in the field in Section 2. In Section 3, the approach taken to address the given forecasting challenge is explained. Our machine-learning categorization models' outcomes are presented in Section 4, with explanations aimed at clarifying the implications of the findings thrown in. Lastly, our research is summarized in Section 5 with closing thoughts.

2. Literature Survey

Over the past ten years, there has been a sharp increase in interest in research on trading software for the Bitcoin market that makes use of blockchain technology. This emerging discipline offers fresh approaches to persistent problems in the trading environment by fusing the domains of finance, technology, and cryptography. We examine important academic publications that examine the complexities, opportunities, and drawbacks of this kind of software in this overview of the literature.

An insightful summary of blockchain technology and its uses in Bitcoin trading software is given by Zhang et al. (2018). A decentralized and unchangeable ledger system powers cryptocurrencies like Bitcoin: blockchain technology. The authors analyze its workings and highlight how it might improve trade transactions' security, trust, and transparency. They investigate a range of blockchain-powered software solutions, from algorithmic trading platforms to decentralized exchanges. Zhang et al. provide a solid basis for comprehending the Bitcoin trading software market by clarifying the fundamental concepts and features.

Li et al. (2020), expanding on this framework, examine decentralized trading platforms in greater detail. These platforms are a well-known category of blockchain-based trading solutions. Decentralized exchanges, in contrast to conventional centralized exchanges, function without middlemen, enabling peer-to-peer transactions. Li et al. compare decentralized exchanges to their centralized equivalents, examining the architecture, functioning, and security features of each. They assess the user experience, liquidity, and performance of top decentralized exchanges, highlighting their potential to upend established trading practices.

Automated trading systems are a new frontier in Bitcoin trading software, whilst decentralized trading platforms offer a paradigm shift in trading dynamics. In their thorough analysis of automated Bitcoin trading systems, Kumar et al. (2019) look at the algorithms, tactics, and ramifications of each system. Algorithms are used by automated trading systems to carry out trades automatically in response to preset parameters, like price changes and market indicators. In-depth analyses of the design issues, legal difficulties, and moral ramifications of automated trading are provided by Kumar et al., who provide insightful information on this quickly developing topic.

3. Reproducibility Challenges

We want to reproduce the findings of Mudassir et al.'s work, using it as a standard. By combining internal Bitcoin properties, technical indicators, and Analysis of Principal Components (PCA) or a unique a feature selection method for building a dataset, Mudassir et al. proposed machine learning algorithms for predicting fluctuations in the price of Bitcoin. The study covers three different time periods, however because the Bitcoin market is always changing, the main emphasis is on the period from April 2013 to December 2019.

We have four types of models: Support Vector Machine (SVM), Stacked Artificial Neural Network (SANN), Network of Long-Short Term Memory (LSTM), and analysis of Artificial Neural Network (ANN). Table 1 presents the outcomes of the precise price regression and next-day price classification tasks using an80-20 ratio between training and testing. With an AUC score of 60% and the highest accuracy in the classification job, the SANN emerges victorious.

Nevertheless, disparities in the published results emerged when we used the approach described in this work using the GitHub implementation code that was made available. In particular, the LSTM in the regression job and SANN in classification task were unintentionally coached using the test data. As a result, the evaluation results for their prediction performance on subsequent data were excessively optimistic and overfitting. Table 2 shows how this overfitting significantly affects the categorization task.

Additionally, it was discovered that there was a mistake when the components weren't applied in the PCA phase appropriately. Instead of using the primary components effectively, the models in this work use them as features.

Table 1: summarizes the classification models' accuracy, f1-score, and AUC score as reported by Mudassir et al.

Measures	ANN	SVM	SANN	LSTM
Accuracy(%)	53	56	60	54
f-1 score	0.61	0.53	0.60	0.66
AUC	0.53	0.56	0.60	0.54

Table 2: A comparison between the SANN evaluation metrics published by Mudassir et al. and the metrics we arrived at after taking the overfitting of the model into account

Measures	[SANN (org)]	[SANN (fix)]
Accuracy(%)	60	54
f-1 score	0.60	0.51
AUC	0.60	0.54

Components for data transformation, after which the given data is used to train the model. This results in false characteristics and totally distorts that data used to get the PCA outcomes.

Furthermore, this reviewed research is devoid of thorough information about experimenting with model design and hyperparameter adjustment. Robust hyperparameter optimization is not backed by enough data, and the process-driven derivation of some derived hyperparameter values is not adequately documented. The paper might benefit from using cross-validation in place of the single 80-20 ratio of training-and-testing split and implementing hyperparameter optimization for parameter selection to strengthen methodological rigor. Our analysis of this study highlights the difficulties data scientists encounter when creating accurate and reliable models. In data science, which is a field that is always changing, attempts are made consistently to improve assessment methods. In this instance, we aim to aid in this progress by pointing out prevalent problems and suggesting possible solutions. We applaud the authors of this study for making their models and data freely available to the public, despite the obstacles. Their transparency allowed us to recognize and resolve several process problems. Although we acknowledge that there may be criticisms of our methodology in the future, we believe that the FinTech industry's dedication to openness and transparency in data science will increase the reliability, credibility, and usefulness of underlying models and obtained outcomes.

4. Proposed Work

4.1. Methodologies

The methods suggested in this paper are shown in Figure 1. The process starts with the dataset being created using the features mentioned in Section 3.1. The next step involves applying pre-processing of data to collect, neat and clean as well as produces fresh features for aggregates. During The feature choice phase, pertinent characteristics are taken out of the data in order to train the model later on. The models are trained, the data is scaled, and parameters are determined via hyperparameter optimization and cross-validation during the training phase. Using the trained models in actual trading scenarios is the final phase, which offers a natural assessment of their effectiveness.

4.2. Data Collection

Our goal was to expand on prior research by adding more features to the dataset and classifying them into two primary categories: features that are part of the network of the Bitcoin Blockchain and outside elements that might have an impact on Bitcoin prices.

Internal elements include data about the actual Bitcoin asset and transactions within its Blockchain network. They are well-known for their ability to forecast Bitcoin prices. We scraped data from https://bitinfocharts.com to gather internal Bitcoin features, adhering to the methods of Mudassir et al. [2020]. For every feature, this website provides access to nine technical indicators over five distinct time periods, offering both raw feature values and illuminating signs. We are able to identify statistical elements and underlying interdependencies in the data thanks to these technical indicators. Furthermore, we integrated in-house functionalities obtained from https://data.Bitcoinity.org, an online platform that compiles information from multiple international Bitcoin exchanges. With data from different exchanges, we are able to find previously unknown differences in the information that Bitcoin traders are shown on these platforms, which gives our dataset several new features.

Previous research has included external features, but none at the same time as ours. Examples of these include macroeconomic and sentiment-based aspects [Mai et al., 2018, Lyócsa et al., 2020, Raju and Tarif, 2020], a small collection of stock or commodity indices [Mallqui and Fernandes, 2019, Chen et al., 2020], or both. Additionally, as far as we are aware, currency exchange data has not examined in this particular scenario.

As a major contribution to our work, we aim to improve predictive power by significantly expanding the traditional feature set in the modeling assignment and exploring previously uncharted territory for putative predictive elements.

We used the Yahoo Finance API to scrape stock, commodity, and currency exchange data from https://finance.yahoo.com in order to include external features. This flexible API functioned as a single point of contact for gathering the required external features for each of these categories. A wide range of futures on commodities, stock exchange indexes, as well as conversion rates for currencies that are incorporated within our framework are displayed in Table 3. Our methodology covers a broad a variety of financial, industrial, and food goods, in contrast to previous research that concentrated on monetary commodities like gold. A more thorough description of market influences is made possible by this wider inclusion, which takes into account variables like inflation that could be misrepresented in economic data. Additionally, although earlier research mostly focused on top American stock exchange indices, our study takes more global method for addressing characteristics. Since Bitcoin is a valuable resource that is exchanged globally, our model integrates features from exchanges across the globe. By acknowledging the various currencies and market views connected to Bitcoin trading, this method offers a deeper comprehension of the dynamics of the market.

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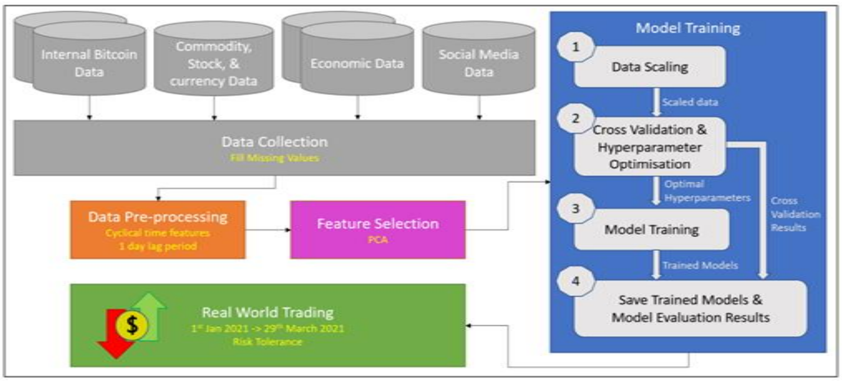

Figure 1: This study's methodology

Table 3: Yahoo Finance's scraped foreign exchange rates, stock indexes, and commodities futures

Commodity Futures		Stock Indices		Currency Exchange Rates
Crude Oil	Soybean Oil	S&P 500 Index	Turkey's BIST 100 index	Euro - GBP
Natural Gas	Corn	Dow Jones Industrial Average	Taiwan exchange index	Euro - Swiss Franc
Gold	Wheat	Nasdaq index	Hong Kong's Hang Seng index	Euro - Japanese Yen
Silver	Oat	NYSE composite index	Singapore FTSE straits index	GBP - Japanese Yen
Platinum	Rough Rice	AMEX composite index	Japanese Nikkei 225 index	USD - Japenese Yen
Palladium	Sugar	Russell 2000 index	Korean Kospi index	USD - Euro
Copper	Cocoa	Euro STOXX 50 index	Indonesian IDX composite index	USD - Canadian Dollar
Aluminium	Coffee	Euronext 100 index	Australian ASX 200 index	USD - Australian Dollar
Lumber	Live Cattle	UK FTSE 100 index	Australian ordinaries index	USD - Mexican Peso
Cotton	Lean Hogs	Irish ISEQ index	Johannesburg top 40 index	USD - Hong Kong Dollar
Soybean Meal		German DAX index	Buenos Aires S&P MERVAL index	
		Belgium 20 index	Santiage IPSA index	
		French CAC index	Mexican MXX index	
		Spanish IBEX index	Toronto's S&P/TSX index	

Integration of economic data from around the world was a key component of our novel feature set. The economic factors were crucial in light of the recent changes in fiscal policy and large monetary expenditure. We used the US Federal Reserve Bank's (FED) http://quandl.com API to obtain important economic metrics. Important information about both EU and non-EU nations was also obtained from https://db.nomics.world/Eurostat.

As a result of social media's significant influence on asset trading, our dataset's final features are centered around sentiment on social media [Štefan Lyócsa and associates, 2021]. The goal was to identify those factors by focusing on Twitter behavior pertaining to bitcoin. We scraped daily counts of tweets about Bitcoin using https://bitinfocharts.com, along with a number of technical indicator characteristics that came from this data. In order to enhance this feature, we scraped tweets related to particular Bitcoin influencers using the Twitter API. This tactic was inspired by Mai et al. [2018], who highlighted that while minorities' tweets and users have a big impact on the Pricing, most tweets relating to Bitcoin are noise. Our access was limited to tweets from Elon Musk due to restrictions imposed by the Twitter API. We attempted to accurately capture Musk's significant impact on Bitcoin values in our dataset by converting his tweets into sentiment-based numerical characteristics.

4.3 Pre-processing of Data

for the period of training is used to filter out values that cannot be interpolated. Unlike the previously Mudassir group [2020]], who use the to fill in uninterpolable missing values column's most typical value, we adopt an alternative approach. Given the sequential nature of the data format as well as Bitcoin's ten-year development, previously indicated method is deemed unsuitable.

When exchange closures result in missing values in exchange data for commodities, stocks, and currencies, we fill volume features with '0' and use forward filling for price features. This entails using the price value from the previous trading day as the value for the current day. The similar method is used for data from economic indicators, for which interpolation is inappropriate since real-world values are unpredictable. We incorporate two cyclical time elements that reflect the day of the month and the week, to improve the way our algorithm perceives time.

In addition, we proposed a period lag feature to symbolize our classification goal, which was motivated by Laboisierre et al.[2015]. This attribute given a '1' or '0' for the one day lag period in the study depending on whether the price has gone up or down from the previous day.

Models for Prediction

Because training set data was so small—just 4,500 training data points total—once for every day, we sensed it was insufficient to build a model that uses neurons. In this study, we choose to investigate less complex models like Bernoulli Naive Bayes (BNB), Random Forest Classifier (RFC), XGBoost (XGB), and Support Vector Machine (SVM) instead of using a neural method. In order to reduce the possibility of overfitting, we carefully used Time-series cross-validation with nesting in our hyper-parameter optimization move, taking advantage of a time-series' in order structure across folds. This method not only keeps our models from overfitting, but it also gives them a useful assessment score. The addition of time-series Integrating cross-validation with the hyper parameter optimization procedure is illustrated visually in Figure 2. We separated the hyperparameter optimization into two stages due to computational constraints. For numerical values, Bayesian Optimization was used, while for categorical values, grid search cross-validation was applied. We used the selected hyper parameters on which to develop our ultimate prediction models for complete datasets after determining the best hyper parameters as well as calculating the metrics for cross-validation assessment. This final model lays the groundwork for our assessment through actual trading by capturing the data's whole predictive power.

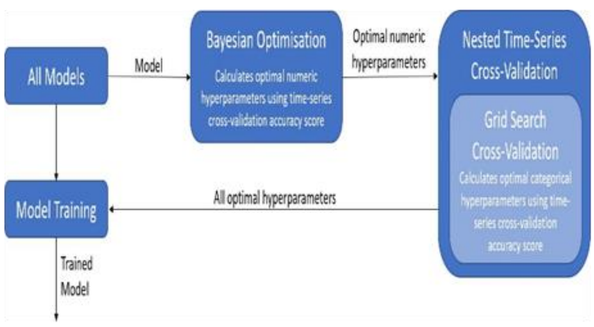

Figure 2: This study's hyperparameter optimization procedure.

5. Result Analysis

5.1. Accuracy of Price Direction Forecast

Using nested cross-validation, we first assessed how well our categorization models performed, noting measures like recall, accuracy, precision, and F1 for its optimal model configurations. Although an ideal model maximizes each of those measures, hyper parameters are often optimized for accuracy. Our accurate and well-validated predictions of the price of Bitcoin changes during the model training time are shown in Table 4. These findings were obtained using three datasets, each of which used a particular number of PCA components to account for different degrees of variance in the original data. SVM was shown to be the best performer across these datasets, with a 56% accuracy rating and a 0.716 F1 score, after training upon the dataset that explained approx. of the 95% variance in the actual data. RFC came in close second, scoring 55.7% on average for cross-validation accuracy using the same dataset.

We used AutoML as a sanity check to make sure our procedure was rigorous. Our data was loaded by AutoML, which then scaled it, identified important features, and repeatedly assessed the models in the pipeline to identify the best one. With 57% on average for cross-validation accuracy, the Naive Bayes Bernoulli (BNB) model was chosen from AutoML process. The validity of our conclusions was supported by the tight alignment of this score with the outcomes of our hyperparameter optimization and cross-validation procedure.

Feature Significance

After establishing our technique and obtaining assessment ratings, we focused on assessing the performance difference between our characteristics and those mentioned in the study by Mudassir et al. [2020]. Remarkably, despite significantly expanding our feature collection, there was no discernible difference in the stated evaluation metrics when we substituted our characteristics with those used in their study. We carried out a thorough analysis of feature importance in order to comprehend this surprising result, and the results showed how important the technical indicators were when combined with the features in the previous study.

Measures	Expl. var(%)	[SVM]	[XGB]	[RFC]
80.0		55.9	54.7	54
Acc. (%)	90	54.9	55	55.7
95		56	53.9	55.7
80		0.716	0.654	0.687
F1-Score	90	0.69	0.688	0.707
95		0.716	0.441	0.704
80		0.56	0.56	0.556
Precision	90	0.552	0.56	0.56
95		0.56	0.349	0.562
80		1	0.833	0.911
Recall	90	0.938	0.907	0.964
95		1	0.6	0.947

Table 4: shows the metrics used for evaluation of cross-validation of every model following it was developed using datasets that retained the various degrees of clarified variation from initial information.

The analysis revealed that 77.75% of the top 200 most important features were indications of technical nature. This underscores remarkable technological indicators' capacity for prediction and suggests a potential avenue for future research—exploring the combination of comparable characteristics paired with pertinent technical indications to enhance model performance.

5.2. Trading System Performance

Following a three-month trial period in the actual world in which we evaluated our models employing the assigned trading approach, the models produced an average profit of $24,000. An examination of the prediction scores revealed a propensity for a purchase and hold methodology, while trading the market for bitcoins, which is at odds with the anticipated active trading technique to take advantage of market volatility. Surprisingly, this tactic worked incredibly well throughout the allotted time, as the price of Bitcoin increased by 86% from its beginning value of over $28,000 to over $52,000 at the conclusion, changes in the risk tolerance parameter revealed changes in the trading profit and loss values of the models, even though most of them reliably predicted the naive class. Although this element would be determined by a trader's individual objectives in a real-world scenario, for example we investigated its effect on profitability in this study. Traders with lower risk tolerance are less likely to buy or sell at any particular moment. We built ROC curves by averaging the probabilistic prediction outputs, and then we used geometric mean ratings for find best categorization thresholds for every model. After normalization, these limits were converted into a risk tolerance parameter.

The profit and loss figures for the chosen models throughout the given time period with a 30% risk tolerance are shown in Figure 3. The graph shows that the The Random Forest Classifier and the Naive Bayes Bernoulli (BNB) model fared better than the buy-and-hold trading approach. The buy-and-hold strategy's $24,000 profit was surpassed by the BNB model's over $27,000 profit. This discrepancy indicates a 12.5% relative profit for the BNB model for the quarter. Although the outcomes of this adjusted risk parameter were beneficial, the majority of risk tolerance values were not able to exceed the basic Buy and hold tactics.

Figure 3.0: Using their predictions, the prototypes computed the gains and losses throughout time in relation to the expense of Bitcoin while we trade with a tolerance for 30% risk

Conclusion & Future Work

Our work aims for contribution to the body of publications written by presenting an innovative standard for the price of Bitcoin prediction which will act as a basis for upcoming studies. We address the issues of reproducibility in the data science sector, emphasizing how important it is to have a strict machine learning pipeline in order to guarantee correct reporting of model outcomes. Our study includes a more practical assessment based on actual trading, highlighting the impact of a trader's risk appetite on returns. Even though our models displayed a trading pattern similar to a buy-and-hold strategy, this method produced impressive results during the assessment period. When a customizable risk tolerance parameter was added to our Bernoulli Naive Bayes model, the quarterly return outperformed a buy-and-hold strategy by 12.65%.

While our extensive feature set augmentation did not significantly impact predicting performance, there is still much room for further research, especially when it comes to exploring the use of technical indicators. Additional research on the integration of social media sites like Reddit, Facebook, 4chan, and Twitter could greatly improve predicting accuracy. Furthermore, integrating online learning into trade evaluation should strengthen the metric's validity and yield a more precise measure of a model's profitability in the volatile real-world Bitcoin market.

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