Volatility Prediction in Cryptocurrency Using NFTs

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The cryptocurrency market has evolved in unprecedented ways over the past decade. However, due to the high price volatility associated with cryptocurrencies, predicting their prices remains an attractive research topic. While many researchers have focused on predicting cryptocurrency prices, there has been relatively little attention given to the latest trend in blockchain applications, specifically non-fungible tokens (NFTs). In this study, we have prepared a dataset comprising NFT sales and transaction data, along with information from other cryptocurrencies. This dataset is utilized to forecast the future price of Bitcoin using several machines learning models, including Linear Regression, Random Forest, and XG Boost. The results highlight the prediction accuracy of these models. Among the three, the Random Forest regressor demonstrates the highest accuracy, followed closely by the XG Boost regressor and Linear Regression. These findings may assist investors in making informed decisions when investing in cryptocurrencies.

Keywords: Cryptocurrency; Machine Learning; NFT; Price prediction; Volatility

Introduction:

Cryptocurrencies were first introduced in 2009 when Satoshi Nakamoto, the creator of Bitcoin, announced it as the first decentralized medium of exchange. All cryptocurrencies are significant applications of blockchain technology, which offers a more secure method for creating applications. They have gained widespread recognition due to the secure nature of transactions and their decentralized operations [1]. Initially, Bitcoin was not very popular at its inception. It began the year 2017 priced at $1,000 but attracted significant attention as it soared to $20,000 by December 2017. Given Bitcoin's price volatility—much greater than that of traditional currencies—it is perceived as an attractive yet high-risk investment option [2].

While cryptocurrency shares similarities with stocks, there are distinct differences. Machine learning (ML) algorithms are employed in various price prediction methods for stock values. However, the factors influencing cryptocurrency are unique; they are not directly affected by corporate or government announcements and do not operate in the same way as traditional stock exchanges [3].

Most cryptocurrencies are generated through a process called mining, where computers solve complex puzzles to validate network transactions—a method that can be energy-intensive. Those who own these computers earn newly minted cryptocurrency as a reward. Other cryptocurrencies, aside from Bitcoin, create and distribute tokens through various means, many of which have a significantly lower environmental impact [4].

Cryptocurrency prices are highly volatile, with data from 2016 to 2023 showing significant fluctuations. The changing value of Bitcoin is illustrated in Figure 1. As more individuals invest in cryptocurrencies, accurately predicting future prices becomes increasingly important. Therefore, substantial research efforts are necessary to develop effective methods for cryptocurrency price prediction using various techniques, including statistical analysis, machine learning, and deep learning [4].

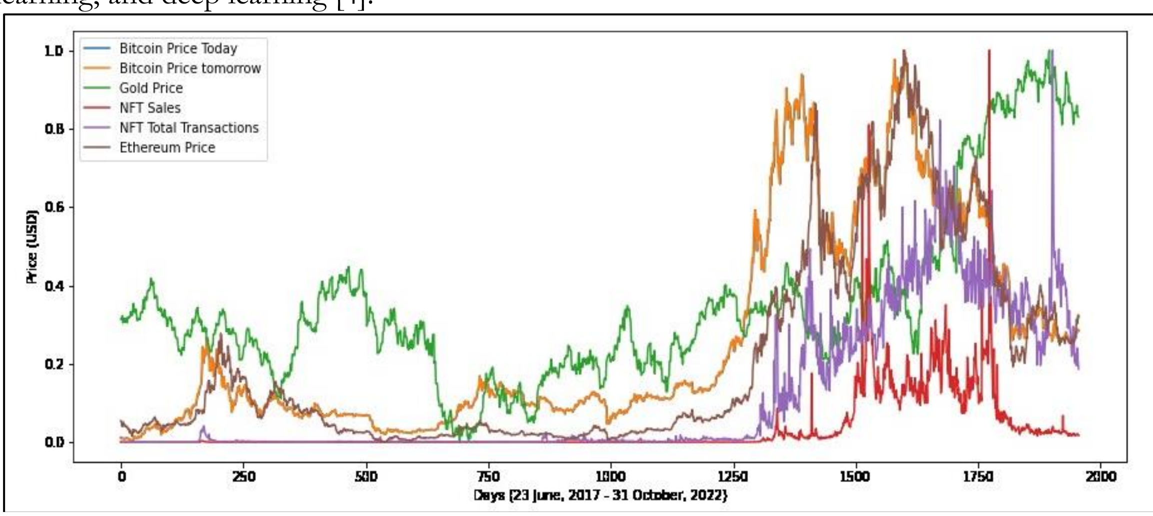

Figure 1. Historical trends of Bitcoin price

Objective:

"The purpose of this article is to predict the price of Bitcoin, the largest cryptocurrency by market capitalization, using various machine learning techniques. Bitcoin's price has exhibited dramatic fluctuations on both a daily and long-term basis, with these price changes influenced by numerous factors, creating greater opportunities for profit [5].

Numerous studies have attempted to predict cryptocurrency prices. In [6], the authors utilize existing machine learning algorithms to forecast cryptocurrency prices but find no correlation between pricing data and other market parameters. Similarly, in [7], the authors enhance the cryptocurrency price data with dollar prices to improve prediction accuracy, yet they acknowledge that incorporating additional factors may also be beneficial. Additionally, the study in [8] employs machine learning models without augmenting the pricing dataset.

In this research paper, we focus on predicting prices by considering multiple factors. Notably, non-fungible tokens (NFTs) play a crucial role, as they are exclusively traded using cryptocurrencies. Furthermore, the price of gold is another significant factor influencing cryptocurrency price predictions. Thus, this paper aims to advance existing research by integrating these additional features to achieve improved outcomes. Multiple results are generated based on the risk level that an investor is willing to assume."

Related Work:

There are various types of cryptocurrency price analyses, including statistical [9][10] and time series analyses. Many researchers have employed statistical models such as Autoregression (AR), Moving Average (MA), Autoregressive Integrated Moving Average (ARIMA), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) to forecast cryptocurrency prices. Additionally, numerous studies have utilized machine learning and deep learning techniques to predict prices based on historical data. In this section, we will discuss articles that focus on both statistical-based predictions and machine learning/deep learning-based price forecasting for cryptocurrencies.

Statistical Based Prediction:

The ARIMA model is widely used for predicting time series data and has proven effective for forecasting Bitcoin prices. The pricing data exhibits seasonality and patterns that can be leveraged to predict future values [9]. In [9], the authors applied the ARIMA model to 1,362 observations collected from CoinDesk over 534 days. The mean percentage error (MPE) was calculated, indicating that the ARIMA model achieves an accuracy of 60-70 percent. Specifically, the autoregressive integrated moving average (ARIMA) model was utilized to analyze Bitcoin data from 2013 to 2017. In [10], the authors associated daily closing prices with other parameters in the dataset, such as market capitalization and transaction volume, and identified a pattern of predictive techniques that yielded more accurate results. Using the ARIMA model, Bitcoin prices were forecasted with an accuracy of 90.31 percent, outperforming the autoregressive (AR) and moving average (MA) models, which achieved accuracies of 89.24 percent and 87.58 percent, respectively.

While statistical models like ARIMA, AR, and MA are useful, they have limitations compared to machine learning models when it comes to time series analysis and predicting complex patterns, such as Bitcoin's price movements. Traditional statistical models typically assume linearity and stationarity, which do not apply to Bitcoin's non-linear and dynamic behavior. Moreover, manual feature engineering can be challenging in capturing all influencing factors, whereas machine learning models can automatically extract relevant features from the data. Additionally, the non-stationary behavior of Bitcoin, including trends and volatility shifts, presents significant challenges for traditional statistical models.

Machine and Deep Learning Based:

Machine learning models exhibit superior predictive power by learning from extensive datasets, identifying hidden patterns, and adapting their parameters for more accurate predictions. This advantage is especially valuable in cryptocurrency markets, which are influenced by multiple factors.

Twitter sentiment, for instance, has a notable impact on Bitcoin prices [11]. In [11], the authors explored the relationship between tweet sentiment and price direction, predicting Bitcoin's price using Random Forest Regression with an accuracy of 62.48%. Their experiments included various regression-based algorithms, such as linear regression, boosted decision tree regression, neural network regression, and Bayesian linear regression, as detailed in [2].

The dataset spans 1,066 days, providing daily low, high, opening, and closing prices for Bitcoin. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are effective techniques for challenges like Bitcoin price prediction. In [12], RNN, LSTM, and Gated Recurrent Unit (GRU) models were evaluated, with GRU emerging as the top performer. The GRU model achieved an average precision of 94.70%, surpassing the RNN and LSTM models, which recorded 52.0% accuracy. Baseline neural network models for predicting Bitcoin price movements in both the short and long term are discussed in [13], where the Multi-layer Perceptron (MLP) and RNN were utilized.

The developed models were capable of predicting price changes over time frames ranging from 2 days to 60 days, with results indicating that long-term predictions generally outperform short-term forecasts. The MLP model achieved superior accuracy, precision, and recall, with scores of 81.3% accuracy, 81% precision, and 94% recall. Additionally, MLP and LSTM models were employed to forecast prices for Bitcoin, Ethereum, and Litecoin [14]. The author trained the model using historical data from the preceding seven days, incorporating historical data, blockchain network information, and Twitter sentiment datasets, which resulted in a 7.41% improvement over deterministic neural network models.

An ensemble-enabled LSTM model incorporating various time intervals for Bitcoin price prediction was proposed in [15]. This approach demonstrated how different LSTM layer configurations could yield varying outcomes by training on diverse time intervals. The model predicted Bitcoin prices with 96.86% accuracy while achieving a Root Mean Square Error (RMSE) of 31.60, outperforming others in volatile market conditions.

Reinforcement Learning (RL) has also been employed to predict the prices of Litecoin and Monero, measuring performance using evaluation metrics such as RMSE, Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The proposed model exhibited significantly improved results, yielding lower RMSE, MSE, MAE, and MAPE for both cryptocurrencies [16]. In [17], a multi-head attention-based transformer encoder-decoder model was applied to Dogecoin price data for future price predictions. This model achieved 98.46% accuracy and a 0.8616 R-squared value, evaluated using MAE.

Additionally, the price of Dogecoin was predicted using LSTM in [18]. The proposed model incorporated historical data along with tweets related to Dogecoin. Experiments revealed that the model performed better when both historical and tweet data were utilized, specifically using only open and close prices along with volume for historical data. The error for the best-performing model was approximately 15%.

Novelty Statement:

From the literature review, we conclude that machine learning and deep learning models may outperform statistical models in predicting cryptocurrency prices. Additionally, combining historical data with social media sentiment tends to yield better results than relying solely on either source. However, the challenge of obtaining social media sentiment data prompts us to explore alternative solutions. Moreover, existing techniques often overlook the impact that changes in one cryptocurrency may have on others.

Furthermore, current studies do not address the latest advancements in Web3, particularly non-fungible tokens (NFTs). To the best of our knowledge, NFTs have not yet been utilized to predict cryptocurrency prices. Given that NFTs are significantly traded using cryptocurrency, there exists an important relationship between the two. Therefore, this study aims to apply machine learning techniques to data sourced from various platforms, yielding valuable insights.

Machine learning models hold immense potential for analyzing and predicting the dynamics of Bitcoin, cryptocurrencies, and NFTs, yet they face unique challenges. Understanding model interpretation is crucial for comprehending the factors that influence prices, trends, and valuations. Additionally, comprehensive datasets are essential for developing accurate models. By addressing these challenges, we empower machine learning models to provide valuable insights within the evolving landscape of Bitcoin, cryptocurrencies, and NFTs.

Material and Method for NFTs Based Price Prediction:

- Given the limited literature addressing Bitcoin price prediction based on NFT data and other cryptocurrencies, we implement an algorithm to investigate the influence of NFT sales and transactions, as well as other cryptocurrencies, on Bitcoin prices. The following steps are undertaken:"- Obtain price data from cryptocurrency and financial platforms, such as Yahoo Finance and Nasdaq.
- Gather NFT data from Cryptoslam.
- Preprocess the data by performing feature extraction to eliminate redundant features and retain only the most important ones.
- Input the processed data into machine learning models to train them for predicting Bitcoin prices.
- Figure 2 illustrates the conceptual framework of the proposed study. This research utilizes three datasets from distinct sources, detailed as follows:
- Price data for Ethereum and Bitcoin.
- NFT sales and transaction data.
- Gold price data.

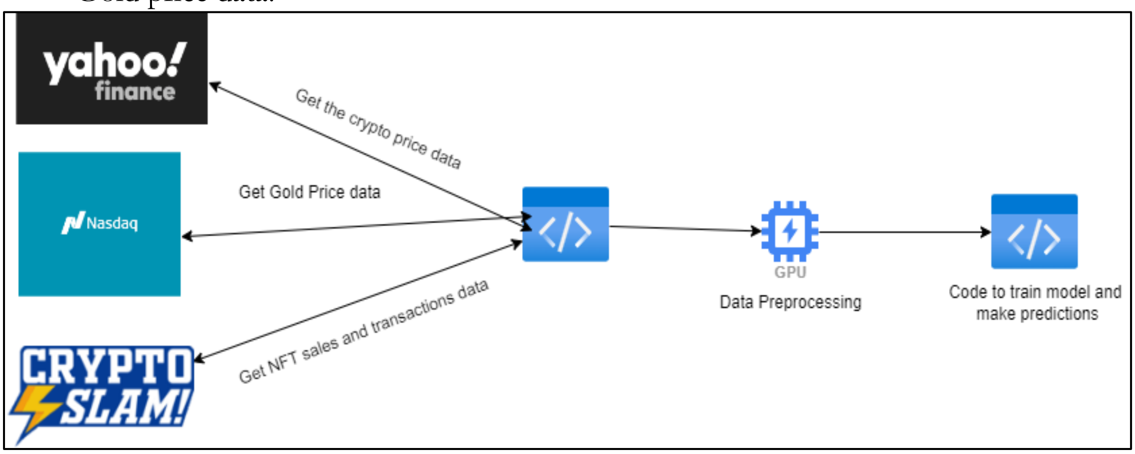

Figure 2. Proposed flow of study

The Yahoo Finance API [19] is utilized to obtain price data for Bitcoin and Ethereum. A Python script running in a Jupyter Notebook processes this data. By providing the cryptocurrency symbol and specifying a date range, we can retrieve the necessary information. This research utilizes 1,957 data points covering the period from June 23, 2017, to October 31, 2022. The NFT global sales data is sourced from Cryptoslam [20], which offers comprehensive NFT statistics. This dataset also consists of 1,957 data points for the same date range, detailing daily NFT sales and transactions. Additionally, gold price data is downloaded from Nasdaq [21], providing historical prices for the same timeframe.

Using these datasets, a consolidated data frame is created that includes only the most relevant features. A new column is added to this data frame, representing the Bitcoin price for the following day, allowing us to train our model based on future price predictions.

After constructing the data frame with the essential features, a correlation heatmap is generated to analyze the relationships between the datasets. Figure 3 illustrates that the Bitcoin price is strongly correlated with Ethereum price and total NFT transactions while showing minimal correlation with gold price and a slightly better correlation with NFT global sales.

In this research, we employ three machine learning models—Linear Regression [22], Random Forest Regressor [23], and XG Boost [24]—and compare their results across four different datasets: NFT sales, NFT transactions, gold price, and Ethereum price. Eight combinations of these datasets are created as input for the models, with all three machine-learning models trained on each combination. The combinations include NFT Sales, NFT Transactions, NFT Sales and Transactions, Gold Price, Ethereum Price, and combinations of Gold Price with NFT Sales and Transactions.

As mentioned in the Introduction, there exists a correlation between the price of Bitcoin and other market trading options, such as gold price, NFT price, and dollar price. To our knowledge, previous studies have not thoroughly investigated the relationship between these market factors and Bitcoin. Therefore, we aim to utilize these parameters to enhance our Bitcoin price prediction.

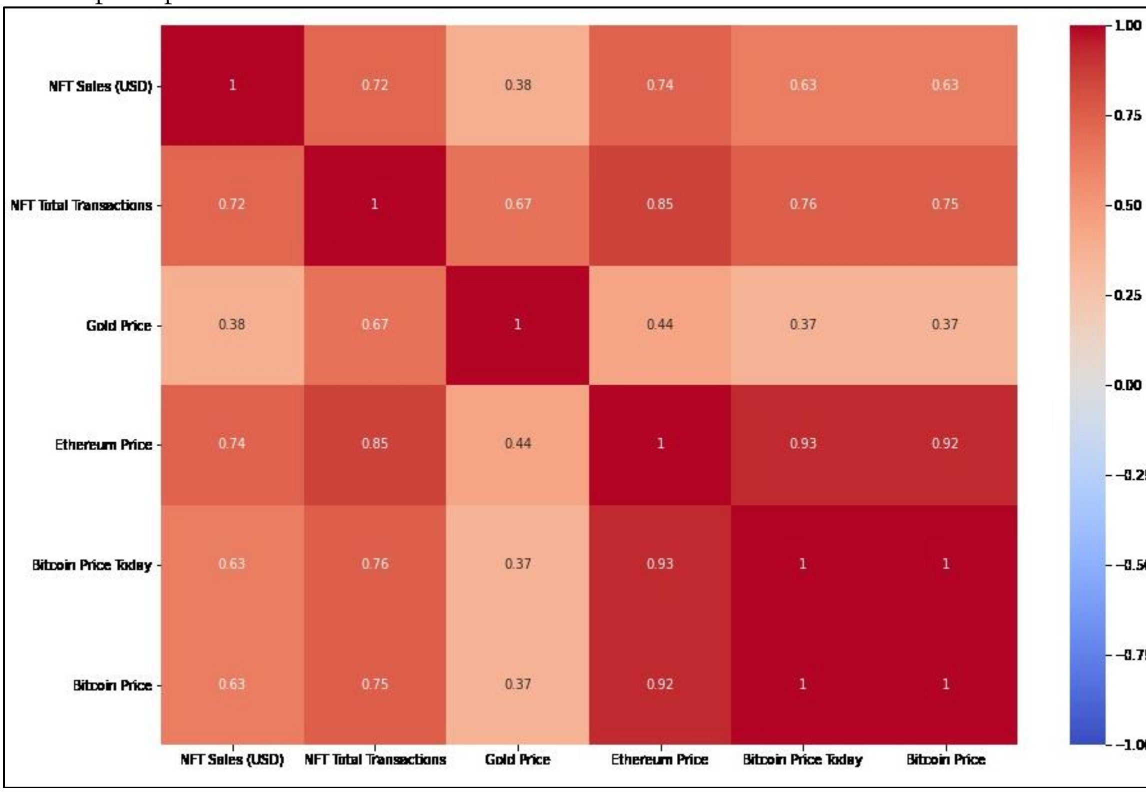

Figure 3. Correlation heatmap

Evaluation Results:

This section outlines the experiments conducted using the proposed methodology and presents the results. These findings will help us assess whether our approach has successfully improved the prediction accuracy of Bitcoin prices.

To evaluate the performance of the machine learning models across various data subsets, three metrics are employed:

- Mean Absolute Error (MAE) [25]
- Mean Squared Error (MSE) [26]
- Root Mean Squared Error (RMSE) [27]

Seventy percent of the data is allocated for training, while the remaining thirty percent is reserved for testing. The aforementioned metrics are applied for error calculations across all datasets and machine learning models utilized in this research. Tables 1, 2, and 3 present a comparison of the errors for the Linear Regression (LR), Random Forest (RF), and XG Boost models, respectively.

After obtaining the results from the machine learning models, we visualize the correct and incorrect predictions for each dataset and model. Various error thresholds are also examined to determine how much our predicted values deviate from the actual values, providing insights into the investment risk levels. The bar charts below illustrate the comparison between accurately and inaccurately predicted prices. Predictions falling outside the established error limits are classified as incorrect, while those within the limits are deemed correct. The subsequent subsections provide a detailed analysis of the results.

Table 1. Evaluation Table for Linear Regression

Dataset	MAE	MSE	RMSE
NFT Sales	0.15048	0.04152	0.20377
NFT Transactions	0.11862	0.03066	0.1751
NFT Sales and Transactions	0.1157	0.02953	0.17186
Gold Price	0.19215	0.06106	0.24709
Gold Price, NFT Sales, and Transactions	0.11361	0.02806	0.16751
Ethereum Price	0.06536	0.01086	0.10421
Ethereum Price, NFT Sales, and Transactions	0.06536	0.01016	0.10081
Ethereum Price, Gold Price, NFT Sales and Transactions	0.06464	0.01018	0.10091

Table 2. Evaluation Table for Random Forest

Dataset	MAE	MSE	RMSE
NFT Sales	0.07729	0.01521	0.12333
NFT Transactions	0.08826	0.02118	0.14555
NFT Sales and Transactions	0.05258	0.00812	0.09011
Gold Price	0.12123	0.0486	0.22046
Gold Price, NFT Sales, and Transactions	0.0272	0.00214	0.04624
Ethereum Price	0.06558	0.01177	0.10851
Ethereum Price, NFT Sales, and Transactions	0.02256	0.00184	0.04288
Ethereum Price, Gold Price, NFT Sales and Transactions	0.01507	0.00078	0.02791

Table 3. Evaluation Table for XG Boost

Dataset	MAE	MSE	RMSE
NFT Sales	0.07162	0.01237	0.11122
NFT Transactions	0.08206	0.01639	0.12801
NFT Sales and Transactions	0.05598	0.00805	0.08973
Gold Price	0.14058	0.04419	0.21021
Gold Price, NFT Sales, and Transactions	0.03514	0.00288	0.05366
Ethereum Price	0.05981	0.00879	0.09378
Ethereum Price, NFT Sales, and Transactions	0.0303	0.00247	0.04973
Ethereum Price, Gold Price, NFT Sales and Transactions	0.02279	0.00118	0.03436

Figure 4 demonstrates that linear regression underperformed across all datasets. The plots indicate that neither NFT data nor gold price data significantly contributed to predicting Bitcoin prices when using linear regression. In contrast, Figure 5 illustrates that the Random Forest regressor outperformed linear regression, particularly when applied to datasets combining Ethereum with either gold or NFT data. Similarly, Figure 6 shows that while the XGBoost regressor also outperformed linear regression, it did not surpass the performance of the Random Forest regressor with the same datasets. Notably, both Figures 5 and 6 suggest that the NFT dataset plays a significant role in predicting Bitcoin prices when utilizing the XGBoost and Random Forest models.

The performance results of the machine learning models across different datasets reveal that NFT data—encompassing both sales and total transactions—and Ethereum prices are the two most influential factors affecting Bitcoin prices in our research. Conversely, gold prices appear to have minimal impact on Bitcoin's price. Furthermore, the findings indicate that utilizing all datasets collectively yields significantly better results compared to using any individual dataset or subset alone.

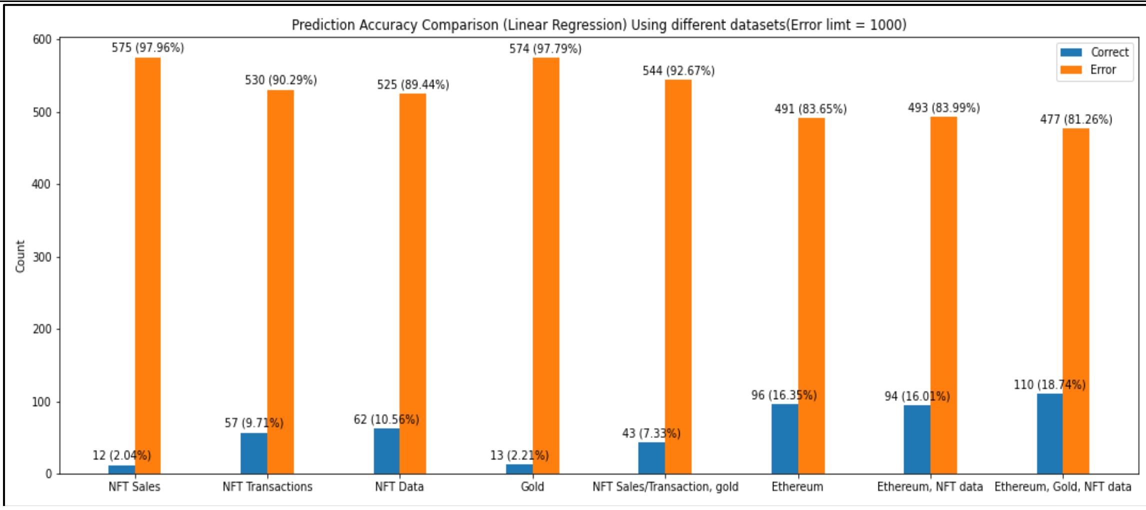

Figure 4. Prediction Accuracy Comparison (Linear Regression) Using different datasets

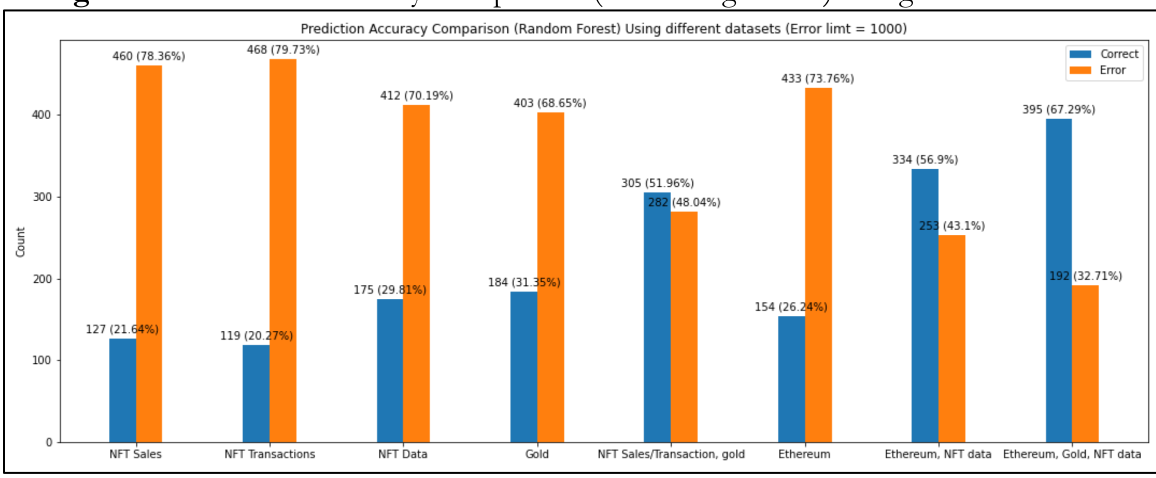

Figure 5. Prediction Accuracy Comparison (Random Forest) Using different datasets

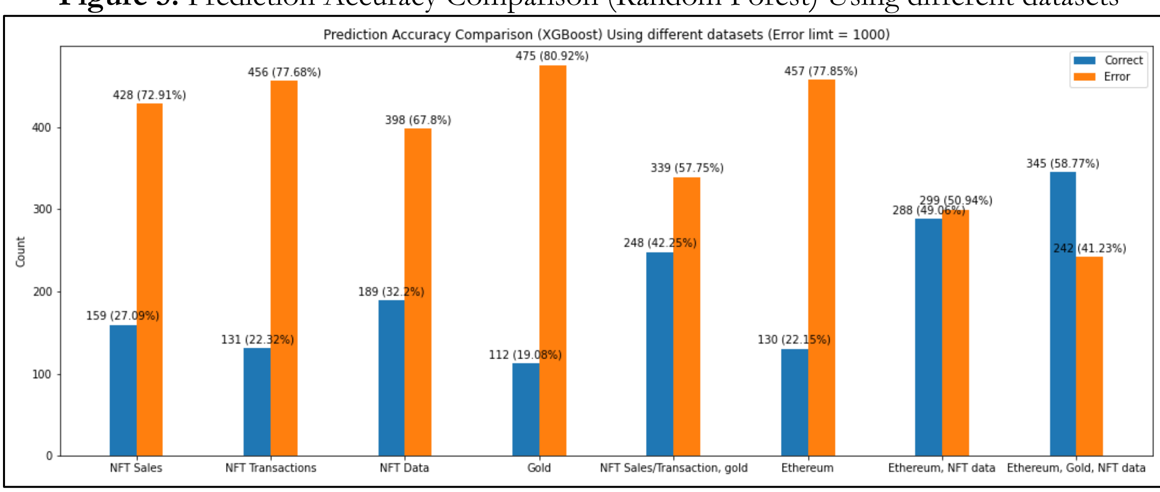

Figure 6. Prediction Accuracy Comparison (XGBoost) Using different datasets

Discussion:

Among the three machine learning models evaluated, the Random Forest regressor demonstrated the highest performance, followed by the XGBoost regressor and linear regression. The Random Forest model predicts Bitcoin prices with greater accuracy and fewer errors, as its tree-based structure makes it less sensitive to variable scaling. When comparing our results with previous work by Sang-Ha Sung and Jong-Min Kim [28], which predicted Bitcoin prices using Ethereum and Litecoin closing prices, we find that our research outperforms their findings. In their study, which utilized data from May 2018 to May 2022, they employed ARIMA and artificial neural network models to predict the log-return price of Bitcoin. In contrast, our approach, which integrates Ethereum data with NFT sales and transaction data, along with gold price as features, yields superior results when training a Random Forest model to predict Bitcoin prices.

Conclusion and Future Work:

This research paper leverages the latest application of blockchain technology, non-fungible tokens (NFTs), to predict Bitcoin prices. Additionally, it incorporates Ethereum, the second-largest cryptocurrency, to enhance the accuracy of the predictions. Our findings support the hypothesis that fluctuations in one cryptocurrency can influence the prices of others; in this case, changes in Ethereum's price significantly affect Bitcoin's price. By utilizing NFT global sales data and Ethereum prices as inputs, we achieved satisfactory prediction results for Bitcoin. This approach could also be applied to forecast prices for other cryptocurrencies.

For future work, we suggest focusing on prominent NFT collections, such as Crypto Punks and Bored Ape Yacht Club, rather than relying on global sales data from all NFTs. These well-known collections account for a substantial share of the market in terms of sales and transactions. Furthermore, instead of including all NFT sales and transactions across various cryptocurrencies, we could refine our dataset to concentrate solely on those associated with specific cryptocurrencies.

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