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Research Article

Using Advanced Machine Learning Techniques to Predict the Sales Volume of Non-Fungible Tokens[a]

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Non-fungible tokens (NFTs) are a type of digital asset based on blockchain that contain unique codes verifying the authenticity and ownership of different assets such as art pieces, music, gaming items, collections, and so on. This phenomenon and its markets have grown significantly since the beginning of 2021. This study, using daily data between November 2017 and November 2022, predicts the volume of NFT sales by utilising Random Forest (RF), GBM, XGBoost, and LightGBM methods from the community machine learning methods. In the predictions, several financial variables, including Gold, Bitcoin/USD, Ethereum/USD, S&P 500 index, Nasdaq 100, Oil/USD, Euro/USD, and CDS data, are treated as independent variables. According to the results, XGBoost is found to be the best prediction method for NFT market volume estimation concerning several statistical criteria, e.g., MAE, MAPE, and RMSE, and the most significant influential feature in determining prices is the Ethereum/USD exchange rate.

JEL codes: G12, C53

Keywords: Financial assets, Non-fungible tokens, Machine learning

1 Introduction

Recently, non-fungible tokens (NFTs) have become intriguing assets in the portfolio preferences of investors alongside traditional investment instruments. Each NFT represents a unique digital item and is identified with a unique identity based on blockchain technology. NFTs represent various assets, such as artwork, digital collections, music tracks, game items, and virtual properties. The most significant feature of an NFT is its non-fungibility, meaning that one NFT is not equal to another and is non-interchangeable.

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In contrast to Bitcoin (BTC) and Ethereum (ETH), NFT investors do not possess a tangible asset. Blockchain technology is the foundation for NFTs and cryptocurrencies, which are digital assets. Although cryptocurrencies and NFTs share many commonalities, they also exhibit distinct differences. As opposed to NFTs, cryptocurrencies are generally interchangeable and equivalent to one another. An NFT representing an artwork cannot be exchanged for another NFT or a similar asset. Another distinction is that cryptocurrencies function as payment methods, while NFTs typically represent digital goods. The equilibrium between market demand and supply typically defines the valuation of cryptocurrencies, whereas NFTs generally gain value through the attributes of distinctiveness, scarcity, and market demand associated with the artwork or other digital assets they embody.

NFTs have garnered attention in recent years due to the various factors affecting their prices. The literature has conducted various studies to understand the pricing dynamics of these unique digital assets. According to econometric studies (e.g., Aharon & Demir, 2022; Maouchi et al., 2022; Yousaf & Yarovaya, 2022; Dowling, 2022; Osivand & Abolhasani, 2021; Ante, 2022), the prices of cryptocurrencies, commodity prices (gold, oil, natural gas), and other assets, such as blockchain and exchange rates, and NFT market participants (buyers and sellers) are the main factors affecting the prices of NFTs.

By considering the unique characteristics of NFTs, forecasting their sales volume is crucial, as it allows for the analysis of a particular NFT's distinct attributes and level of popularity. As the correlation between the market value of NFTs and their sales volume is evident, predicting the market volume of NFTs is also important in order to comprehend the potential fluctuations in the value of artworks, digital collections, and other digital assets. This is the primary motivation for this study. In this respect, this paper aims to forecast the Global Sales Volume Index of NFTs using machine learning (ML) methods and compare the performances of four different ML methods algorithms: so-called Random Forest (RF), GBM, XGBoost, and Light GBM, using several financial assets as explanatory variables.

Recently, ML algorithms have been increasingly used to predict and understand the dynamics of NFT prices in the field of time series due to their approaches that allow prediction without the need to examine stationarity. Research employing ML algorithms has demonstrated the ability to forecast NFT collection prices by considering factors like NFT visual features, social media keywords, and the impact of cryptocurrencies (Nadini et al., 2021; Fridgen et al., 2023; Luo et al., 2023; Dowling, 2021). While studies are predicting NFT prices using ML methods, there has yet to be a study using these methods to predict sales volume with financial assets.

The plan of the paper is as follows: In Section 2, the literature review is given. Section 3 introduces the method and data set, and Section 4 explains the application. Finally, the main findings are summarized, and the potential policy implications of the empirical results are considered in Section 5.

2 Literature Review

Since gaining popularity in 2021, many studies have analyzed NFTs. Some studies examining the relationship between NFTs and financial assets investigated the mutual relationship between NFT sales and the pricing of BTC and ETH. For instance, Osivand & Abolhasani (2021), as encompassed in this paper, examined the relationship between Wallet Count, ETH, BTC, and NFT sales values using Granger causality tests, demonstrating that a shock in BTC price triggered an increase in NFT sales. Furthermore, the authors showed that the price of BTC Granger-causes NFT sales, the price of ETH Granger-causes NFT Wallet count, and the price of BTC is Granger-caused by the price of ETH. Granger causality analysis does not reveal the direction of these relationships, but it is noteworthy that cryptocurrency pricing influences NFT markets.

Ante (2022)'s study investigated the relationships between NFT sales, NFT users, and BTC and ETH pricing. Utilizing NFTs and cryptocurrencies and employing Vector Error Correction Models (VECM), they explored the relationship between these two markets by investigating the direction of the relationship using impulse response functions. The study concluded that the larger-scale cryptocurrency markets influence the growth and development of the smaller-scale NFT market. Starting from the premise that the NFT market emerged from cryptocurrencies, Dowling (2022), examining the relationship between NFT pricing and cryptocurrency pricing, showed limited transmission between cryptocurrencies and NFTs using the spread index; however, wavelet coherence analysis indicated common movements between the two market groups, despite low volatility transfers between NFTs and cryptocurrencies. His study suggests that cryptocurrency price movements could provide insight into NFT pricing models. Aharon & Demir (2022) examined the interconnection between NFTs, ETH and financial assets, gold, bonds, stocks, oil, and the USD index in their study. The study's static analysis showed that NFTs had only weak interactions with the financial assets examined, whereas its dynamic analysis indicated that NFTs had some similarities with gold and the USD index in terms of risk during the COVID-19 epidemic. NFTs, priced in the cryptocurrency ETH, have presented a contrasting overall connectivity dynamic, particularly during the COVID-19 crisis. Yousaf & Yarovaya (2022) added a different dimension to studies in this field by examining the return and volatility relationship between new digital assets such as NFTs, Decentralized Finance (DeFi)[1], and other assets (oil, gold, BTC, and S&P 500) using the Time-Varying Parameter Vector Auto Regression (TVP-VAR) method. Additionally, the study used the BEKK-GARCH[2] model to estimate optimal weights, hedge ratios, and hedge effectiveness for market pairs. Overall, the analysis results emphasized that NFTs and DeFi digital assets are relatively separate from traditional assets, and during the COVID-19 pandemic and the initial stages of the 2021 cryptocurrency bubble, dynamic return and volatility correlations became higher.

Studies have shown that the relationship between NFTs and financial assets is multifaceted. The current findings indicate a close connection between the NFT and the cryptocurrency markets but a limited association with traditional assets. In summary, while some studies use ML methods to predict NFT prices, there has yet to be a study predicting sales volume using these methods. This is significant because it provides a way to measure market demand and liquidity for an asset. The prices of financial assets often change based on demand and supply balance. Therefore, the sales volume of an asset is an indicator of its demand. Thus, the sales volume of an NFT reflects how much demand it receives and how liquid it is. For all these reasons, forecasting NFT sales volume is essential for understanding market behavior and predicting prices. These predictions will help investors determine their strategies and understand future trends in the NFT market.

[1] DeFi is blockchain finance without intermediaries, using smart contracts for financial services.

[2] Baba, Engle, Kraft, and Kroner Generalized Autoregressive Conditional Heteroskedasticity.

Besides econometric models, researchers have employed ML algorithms to comprehend and forecast NFT prices, as they can make predictions even when the series is not stationary. Stationarity means that the statistical properties of a time series do not change over time. However, changing properties of financial time series over time make them non-stationary. When we examine the related literature in terms of ML techniques, Zheng (2022) predicted NFT prices using a two-stage ML and end-to-end deep learning approach, utilizing visual and non-visual information of 9,045 NFTs on OpenSea, which is a marketplace where you can buy and sell NFT artworks. Their findings suggested that the visual aspect of NFTs impacted price. However, this effect could have been more substantial than some non-visual information, such as total past bids and the collection the NFT belonged to. Similarly, Nadini et al. (2021) examined the predictability of NFT sales using ML algorithms and emphasized the importance of historical sales data and visual features in predicting NFT prices. Wang & Lee (2023) used ML approaches to forecast fluctuations in NFT sales prices and demonstrated the potential of ML in predicting trends in the NFT market. These studies generally focused on the visual aspects of NFTs, whereas some other studies (e.g., Luo et al., 2023; Fridgen et al., 2023; Dowling, 2021) have shown that factors such as sales history, visual features, and the influence of cryptocurrencies can predict NFT prices.

However, it is essential to consider sales volume and predict NFT prices. Sales volume reflects the popularity and demand of an NFT. Intense buying and selling of an NFT indicates potential interest and can influence its price. Additionally, sales volume determines the bargaining potential and liquidity of an NFT. High sales volume can provide a more dynamic market with more buyers and sellers, which can affect price movements. However, the factors determining the price of NFTs are complex and varied. Therefore, more than focusing solely on visual features may be required to understand the entire market. Considering sales volume will provide a more comprehensive view of the NFT market and help make more accurate predictions. Therefore, sales volume should be considered when creating NFT price-prediction models.

In this regard, we have not only predicted NFT market volume, as commonly done in the literature but also compared and discussed the performance of different ML algorithms used in this area. The comparison analysis is the major contribution of our study to the related literature.

3 Method and Data

3.1 Methods

3.1.1 Random Forest

In the Random Forest (RF) algorithm, random samples are selected from the dataset, and a decision tree is constructed for each sample. As each decision tree predicts the test set, predictions ultimately depend on which decision tree solution receives the most votes. When it comes to regression analysis, the outputs of different trees are averaged. In this method, the random generation of independent variables in the decision trees used in the algorithm is one of the key points that create randomness in the RF method.

In the RF algorithm, the Gini impurity of each branch at a node is calculated as

$$Gini \ = \ 1 \ - \ \sum_{i=1}^{C} \ (\pi)^2 \tag{1}$$

where π represents the relative frequency of the observed species in the dataset, and c represents the number of classes.

Entropy is used to determine whether the node used in classifying observations can be split or branched based on the probability of a specific outcome. *Entropy* is calculated using a logarithmic equation by following Aziz et al. (2022).

$$Entropi \ = \ \textstyle\sum_{i=1}^{C} \ -\pi \ log_2(pi) \tag{2}$$

The RF algorithm constructs multiple decision trees through entropy and combines them to achieve a more accurate prediction.

3.1.2 Generalized Boosted Models (GBM)

Boosting algorithms use iterations to turn weak learners into strong learners progressively. These algorithms differentiate from other methods because they consider how weak learners are defined, or in other words, how they define them differently due to the absence of a uniform definition for weak learners. Given that this knowledge is also included in the GBM algorithm, this method is considered one of the most robust ML algorithms and is treated as an enhancement technique.

GBM is a numerical optimization algorithm that aims to find an additive model minimizing the loss function by adding a new decision tree at each iteration stage. In doing so, a new decision tree is fitted to the current residual at each step and added to the previous model to update the residual.

3.1.3 Extreme Gradiant Boosting Model (XGBM)

Among the ML methods used in practice, gradient tree boosting is a prominent technique. XGBoost is a tree-based model developed by Chen & Guestrin (2016). Each new tree improves the errors of the previous ensemble. The primary objective is to combine weak predictors to create a strong predictor to minimize the regularized objective (Sheridan et al., 2016).

XGBoost is one of the most potent regression algorithms known for its high speed and performance. Essentially, the training is conducted using an "ensemble strategy"; when given a molecule with a descriptive vector x_i, an ensemble of trees employs a sum of K different functions to predict the output. In this case, F represents the sets of all possible regression trees:

$$\hat{y_t} \ = \ \phi(x_t) \ = \ \textstyle\sum_{k=1}^{K} \ f_k(x_t) \quad f_k \in \mathcal{F} \tag{3}$$

At each step k, the function f_k maps the descriptive values in x_i to a specific output. This structure is the function that we need to learn, including the tree's structure and leaf scores.

$$\mathcal{L}(\phi) \ = \ \textstyle\sum_i \ l(\hat{y_t}, y_t) \ + \ \textstyle\sum_i \ \Omega(f_k) \tag{4}$$

$$\Omega(f_k) \ = \ \gamma T \ + \ \frac{1}{2} \ \lambda \ ||\omega||^2 \tag{5}$$

In eq. (4), l is a differentiable convex loss function that measures the difference between the estimated ($\hat{y_t}$) and the target (y_t) outcome. In the second part of this equation, the complexity of the model is penalized with the number of leaves in the tree (T) and the vector of scores on the leaves (ω). The most significant factors behind the success of XGBoost are its high predictive power, resilience against overfitting, ability to handle sparse data, and fast execution.

3.1.4 Light Gradiant Boosting Model (LightGBM)

Although the GBM has numerous useful applications, including XGBoost and GBRT (Gradient Boosted Regression Trees), it may not provide satisfactory results in terms of efficiency and scalability when dealing with large feature and data (variable and observation) dimensions in a dataset. The primary reason for this is that, for each feature, all data samples need to be scanned to predict the information gain for all possible split points, which is time-consuming. To overcome this issue, (Ke et al., 2017) proposed the Light Gradient Boosting (LightGBM) algorithm.

In contrast to other algorithms, the LightGBM algorithm utilizes Gradient-Based One-Side Sampling and Exclusive Feature Bundling techniques. The first technique excludes a significant portion of data samples with small gradients and uses only the remaining data to predict information gain. Data samples with larger gradients play a more significant role in calculating information gain.

3.2 Data

The study analyzes daily frequency data of NFT sales volume from 22.11.2017 to 16.11.2022. The data for explanatory variables, including Gold, Bitcoin/USD, Ethereum/USD, S&P 500 index, Nasdaq 100, Oil/USD, and Euro/USD exchange rate are obtained from Investing.com. The CDS data is obtained from the Thomsen Reuters Eikon data system.

Table 1 presents the descriptive statistics for the variables covered in the study, and Figure 1 shows the correlation matrix among the variables. At this juncture, one can examine the magnitude of correlations inside the matrix and detect clusters of binary relationships.

Table 1: Descriptives Statistics of The Variables

Variable	**Mean**	**Standart Deviation**	**Median**	**Min.**	**Max.**
Y	21,728,141.00	45,134,020.00	58,792.00	507.00	514,082,218.00
XAU	1,596.00	249.86	1,678.00	1,174.00	2,064.00
BTC	20,261.00	17,030.81	10,836.00	3,248.00	67,528.00
ETH	1,131.96	1,205.86	478.52	83.81	4,808.38
S&P 500	3,419.00	676.89	3,226.00	2,237.00	4,797.00
Nasdaq	10,320.00	3,132.10	9,596.00	5,899.00	16,573.00
Oil	72.97	29.07	77.64	17.04	128.64
Euro	1.14	0.06	1.14	0.96	1.25
CDS	11.12	3.29	10.73	5.43	25.00

The variables *XAU, BTC, ETH*, and *Oil* represent the values of gold, Bitcoin, ETH, and oil prices in U.S. Dollars (USD) terms. *Euro/USD* is the Euro's exchange rate against the US dollar. *S&P 500* and *Nasdaq 100* represent the performance of the stock markets in the United States. *CDS* denotes the 2-year CDS risk premium of the United States.

Based on Yousaf & Yarovaya (2022), Ante (2022), and Aharon & Demir (2022), it has been concluded that these variables influence the NFT market and have been treated as independent variables in the models. When examining the relationship between the independent variables considered and the volume of NFT sales, it can be observed that investors may turn to gold when economic uncertainty or risk perception increases. This situation may decrease interest in NFTs, leading to decreased sales volume. On the other hand, when the price of Bitcoin rises, demand for NFTs also increases, potentially boosting the volume of NFT sales. With increased Ethereum prices, investors may acquire more Ethereum, leading to investment in NFTs and an increase in NFT sales volume. If the price of crude oil increases, investors may move away from risky assets due to economic weakness, which could reduce NFT sales volume. High stock prices may indicate an increase in investors' risk appetite, which could also increase interest in NFTs and boost NFT sales volume. In summary, economic uncertainty or changes in exchange rates can affect consumers' digital asset trading behavior.

4 Implementation

In order to determine which factor most influences the NFT sales volume in the study, training and test models are created, with 80% of the data allocated for training and 20% for testing all ML models used in the study. Then, predictions are made using ML algorithms that were briefly explained in the previous section, and their performance in predicting NFT prices is compared.

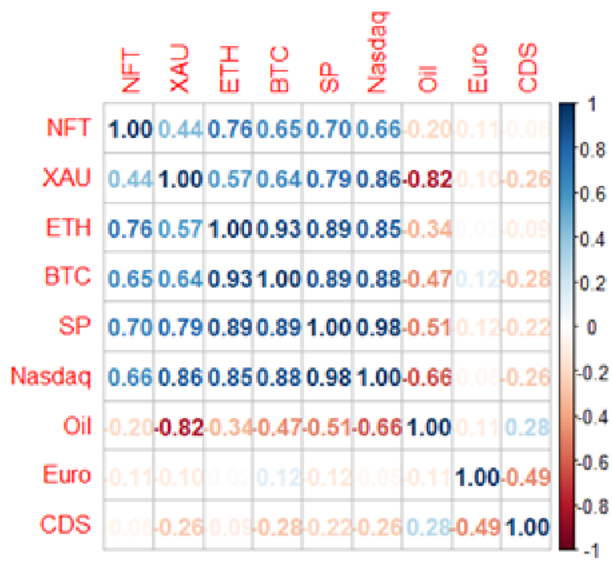
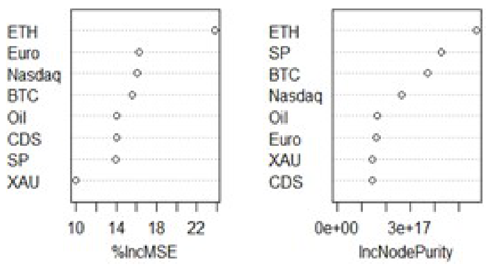


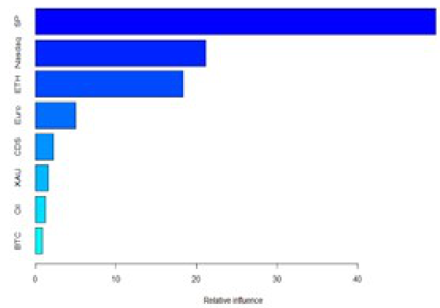
Figure 1: Correlation Matrix Between The Variables

Initially, the model is trained using the designated training dataset, and then its performance is evaluated using the test model. The predictions are compared using commonly used error measurement metrics in the literature, such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).

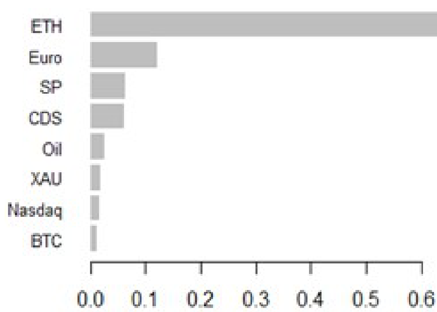
Figure 2 depicts the feature effects identified through the algorithms used in the study, and Figure 3 shows the prediction graphs. Figure 2 illustrates the effects of changes in the value of each feature identified through the algorithms on the model predictions are presented. In other words, it demonstrates how a model explains the relationship between each feature and the target. Figure 3, on the other hand, shows the prediction graphs produced by the ML algorithms. In this context, when the prediction performances are visually compared, it is noteworthy that XGBoost and LightGBM algorithms exhibit the least error and demonstrate the best performance. Relatively, the other algorithms have shown weaker prediction performances.



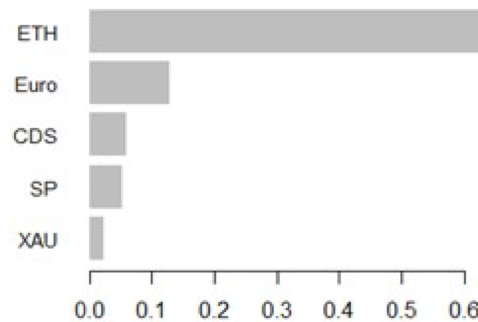
(a) RF



(b) GBM



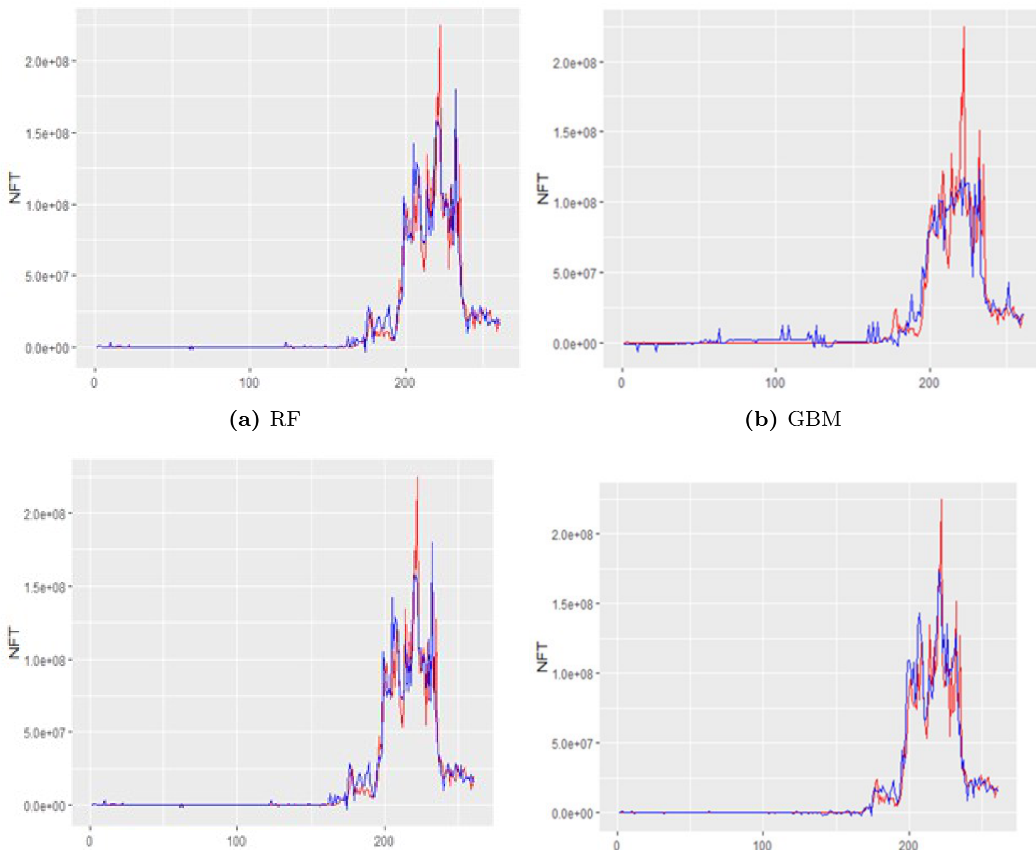
(c) XGBoost



(d) LightGBM

Figure 2: Effective Feature Impacts of RF, GBM, XGBoost and LightGBM Algorithms

When examining the dominant features according to the performance of the algorithms, it is observed in the well-performed XGBoost and LightGBM algorithms that the most essential features are ETH/USD prices, accounting for 60% of the variation, followed by Euro/USD exchange rate, accounting for 10% of the variation. In contrast, other features have varied according to the algorithm. The two most effective features in the XGBoost algorithm are the S&P index and the CDS risk premium, while in the LightGBM algorithm, they are the CDS risk premium, S&P index, and XAU exchange rate. When examining the GBM algorithm, which shows weak performance, it is noteworthy that the most compelling feature for NFT prediction is not ETH/USD prices. In fact, this feature is even ranked third. When the RF and GBM algorithms perform poorly, the impact of certain features varies significantly compared to other algorithms, and this situation is generally perceived as a disadvantage.



(a) RF

(b) GBM

(c) XGBoost

(d) LightGBM

Figure 3: Predictions of RF, GBM, XGBoost and LightGBM Algorithms
Note: The blue (red) line represents the observation series (the prediction of the algorithms).

Although visually inferred insights in Figures 2 and 3 show better prediction performance for the XGBoost and LightGBM algorithms, performance evaluation metrics for the algorithms are provided in Table 2 to confirm this observation. When these metrics are compared, the XGBoost algorithm performs the best, followed by LightGBM. On the other hand, the GBM algorithm is seen as the worst-performing algorithm.

Table 2: Performance Comparison Table of RF, GBM, XGBoost and LightGBM Algorithms

	MSE	MAE	RMSE	R^2
RF	1.577	4,691,045	12,556,042	0.888
GBM	1.891	6,028,783	13,751,767	0.861
XGBoost	1.147	4,060,416	10,707,878	0.916
Light GBM	1.294	4,316,179	11,377,185	0.905

5 Conclusion and Discussion

NFTs are defined as digitally unique assets stored in a digital ledger called blockchain that cannot be replaced. In the literature, NFT pricing is influenced by various factors, such as the characteristics of NFTs, social media membership, and market conditions. Although the determinants of NFTs are not precisely known, their importance can be revealed using machine learning (ML) algorithms.

This paper demonstrates the relative importance of critical financial assets, particularly ETH, BTC, Euro, CDS, S&P 500, Nasdaq, and crude oil prices, on the NFT Global Sales Volume Index. This is achieved by training and testing models using commonly used ML algorithms such as RF, GBM, XGBoost, and Light GBM.

The key findings indicate that XGBoost had superior forecasting performance for NFT sales volume, whereas GBM demonstrated the worst performance. The primary factor influencing NFT sales volume is the ETH/USD exchange rate, followed by the Euro/USD exchange rate. This observation aligns with the research conducted by Osivand & Abolhasani (2021), whereby they posited that ETH catalyzes the emergence of NFTs. Additionally, Ante (2022) argued that cryptocurrency price can provide insights into the theories behind NFT pricing. According to Dowling (2022), a relationship exists between the cryptocurrency and NFT markets. Nevertheless, our study differs from the research conducted by Aharon & Demir (2022), as it demonstrates a limited interaction between the static analysis of the NFT market and financial markets. ML techniques can be used to estimate the sales volume of NFTs in the following stage of building a dynamic model.

The study is based on daily data obtained over a specific period: November 2017 - November 2022. This implies that the results could be influenced by using a wider time range or higher frequency data. The study used many independent variables such as XAU, BTC, ETH, S&P500 index, Nasdaq Index, Oil Price, Euro/USD, and CDS. However, other financial or economic variables, e.g., interest rates, inflation, and GDP growth rate, may also impact NFT sales volume. All of these factors constitute the limitations of this study.

While this study helps to understand the most important features determining NFT sales volume, it also offers some suggestions. These include considering that although the financial assets discussed in the study are indexed to the American Dollar, other countries may also affect the NFT sales volume index. In this context, determining which features affect different countries could be an important determinant for the NFT market. Additionally, future studies could expand the scope of financial assets considered in the study in the specified direction, contributing to a better understanding of the functioning of the NFT market and the expansion of the study in the future.

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