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Price Prediction of the Cryptocurrency from Niche Market Based on Random Forest, LSTM and XGBoost

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Abstract: Cryptocurrency market has striking development and aims to build open, transparent and efficient financial market. More applications are tried to build on blockchain and using cryptocurrency in multiple scenarios, and DeFi ecosystem is set up. Many niche cryptocurrencies related to DeFi market may have wide utility and demand in the future. Therefore, more research is needed to focus these cryptocurrencies and try to establish sturdy price prediction. In this study, two cryptocurrencies, Binance Coin (BNB) and Huobi Tokens (HT), which are rooted in two crypto exchange platform are used for price prediction based on three machine learning models, i.e., Random Forest (RF), Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost). Four prediction windows are selected (1, 3, 7 and 30 days span). The results for different prediction window are compared and discussed. 1 day prediction window outperforms all prediction windows with the average MSE 0.0117. Additionally, RF and XGBoost outperform LSTM with lower MSE and more stable performance, while RF and XGBoost have average MSE 0.0157 and 0.0158 separately. The research tries to predict cryptocurrencies that based on relatively niche market and discuss the performance in comprehensive ways, aiming at providing novel insights into cryptocurrency price prediction.

Keywords: Price prediction, cryptocurrency, DeFi, machine learning, Niche market

1. Introduction

Cryptocurrency market has dramatic development in decades, i.e., started from Bitcoin since 2008, and establish over thousand types of cryptocurrencies from now. Billions of assets are raised on the trust in technological infrastructure called blockchain and aim to build a decentralized financial system without any institution or government [1]. They become new choice of asset allocation of companies and institutions, since its stable supplication and low correlation with other assets [2]. Therefore, cryptocurrencies are great targets for portfolio risk diversification. As the dramatic expansion of cryptocurrencies, more sound financial system was built. Defi, a term with its full name decentralized finance, is a financial ecosystem supplies multiple applications. Asset tokenization was established in this system and these tokens can be used as collateral for loans and to create decentralized derivatives, and also can be included in on-chain investment funds [3]. The more widely use in tokens, the more significant of price prediction will be on these assets. In this research, two tokens, BNB (Binance Coin) and HT (Huobi Token), are used to be the target of price prediction base on three machine learning, Random Forest, LSTM and XGBoost.

Decentralized financial (DeFi), as one of the most popular emerging technological evolutions in global finance, has joined FinTech ('financial technology'), RegTech ('regulatory technology'), cryptocurrencies, and digital assets [4]. Smart contracts in DeFi establish multiple financial activities include lending, trading, deposits, payments and derivatives trading, to create protocols that replicate existing financial services in a more open, interoperable, and transparent way [3]. Some exchange platform also developed their own tokens base on the platform. For instance, Binance Coin (BNB) is the token of the Binance cryptocurrency exchange platform [5]. It can reduce and pay for trading fees on Binance DEX (Decentralized Exchange), or pay for goods and services for both online and in-store purchases (e.g., using Binance Card or Binance Pay). More application also developed, such as hotel and flight booking, or be used in games and DApps on BNB Chain ecosystem. Moreover, it can provide liquidity on Binance Liquid Swap [6]. As for Huobi Token (HT), it is the token of Huobi exchange platform, which is a Singapore-based cryptocurrency exchange and the third-largest cryptocurrency exchange in the world [5]. HT provides benefits like fee discount and rewards for subtokens, or be used in ecological scenarios deposits like voting, or be used for corporate payment like it is available to pay for community service providers and 30+ crypto media [7].

With the spectacular growth in cryptocurrency market with its high volatility and feedback, it is essential to find sturdy model to predict the price of it. A survey of ten years research (2010-2020) in cryptocurrencies price prediction using traditional statistical and machine-learning techniques shed light on that machine learning is better techniques in this field [8]. Multiple machine learning techniques were used, in traditional machine learning model, Random Forest (RF) and ANN outperformed in common. In deep learning fields, LSTM is recommended and it selects the most appropriate information since it can memorize things and manipulate memory. Another decade survey shows that between 2017 and 2022, LSTM is popular and well performed models among deep learning models [9]. They perform better than classical ML models, since they can usually find complex patterns in comparison to the classic machine learning models.

Technical indicators are widely used in conventional asset like gold, stocks and fiat money. However, it can also utilize in cryptocurrency price prediction [10]. Alonso-Monsalve et al. also prove that technical indicators work in cryptocurrency field [11]. Another group of feature selection consider one cryptocurrency's price with its interdependency on other cryptocurrencies [12]. Moreover, some traditional commodities such as gold and oil are mentioned to be considered in the future to enhance the prediction results [13].

This study will investigate the price prediction for two tokens (i.e., Biance coin (BNB) and Huobi Tokens (HT)), which are cryptocurrencies that based on relatively niche market. Give fresh and new examples in cryptocurrency price prediction. Four groups of features selected from previous research based on price prediction of popular cryptocurrencies. In particular, other crypto are used for detected independency relationship between popular crypto and niche crypto. Moreover, traditional commodities and macroeconomics index are chosen for more sturdy performance. 1, 3, 7 and 30 days prediction windows are selected and evaluation metrics include five indicators, which are MAE, MSE, RMSE, MAPE and Median APE. Prediction window and model comparison are discussed and evaluate from two aspects, for which using difference between MAPE and Median APE to evaluate capability of dealing with outliers and using average MSE of all model performance to evaluate ability of average performance. The rest part of the paper develops as follows. Section 2 is about data and methodology. Introducing target and feature selection of data and models to predict price. Evaluation metrices are also given in this part. Section 3 is about results and discussion. Model performance will be listed and compared and give explanation. Section 4 is limitation of research and future work direction. Section 5 is conclusion.

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2. Data and Methodology

2.1. Data and Features

The Data sources come from https://finance.yahoo.com/ and time span from 1/1/2019 to 1/1/2024 (5 years). Two tokens are used as target, Biance Coin (BNB) and Huobi Token (HT). They are tokens based on two cryptocurrencies exchange platform, Biance and Huobi exchange platform, the biggest and the third largest cryptocurrencies exchange platform in the world. 1,3,7,30 days prices will be the prediction time windows. Historical trend from 1/1/2019 to 1/1/2024 (5 years) of two tokens are shown in Fig. 1 and Fig. 2. Features are divided into 4 groups, according to their characteristic. 85 technical indicators are used as features. In the meantime, 10 high market cap and with historical trend data above 5 years cryptocurrencies are chosen, which are Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Cardano (ADA), Tether (USDT), Dogecoin (DOGE), Chainlink (LINK), Tron (TRX) and Filecoin (FIL). In addition, two indices related to macroeconomics are chosen, VIX and IRX. VIX stands for the "Volatility Index," which is a popular measure of market volatility and investor sentiment. It is calculated by the Chicago Board Options Exchange (CBOE) and is based on the implied volatility of S&P 500 index options. IRX, or 13-Week Treasury Bill Index, is a financial benchmark that tracks the performance of short-term U.S. Investors and financial professionals often use the IRX as an indicator of short-term interest rates and market sentiment. Finally, 5 traditional commodities are chosen, which are gold, oil, wheat, natural gas and copper. Both price and volume are considered as features separately.

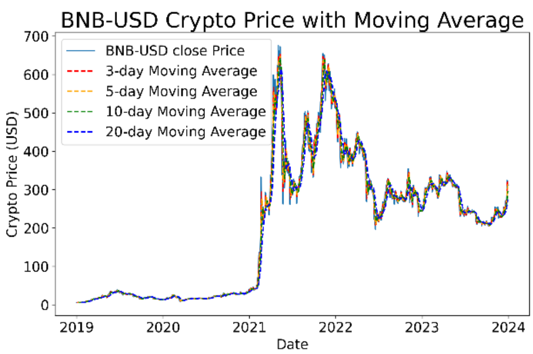

Figure 1: BNB Price (Photo/Picture credit: Original).

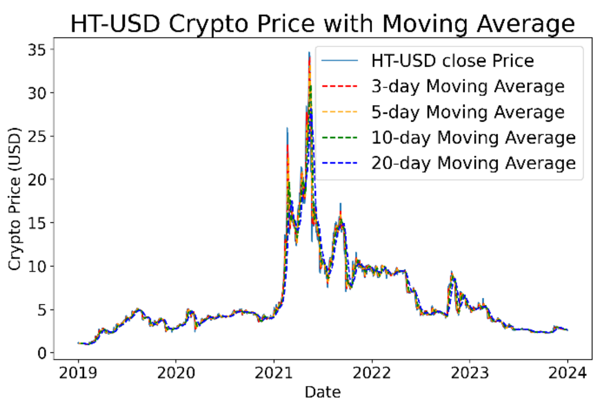

Figure 2: HT Price (Photo/Picture credit: Original).

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2.2. Model

Three models are used to predict price, which are Random Forest, LSTM and XGBoost. A random forest model consists of many decision trees. A forest is created when the model essentially averages the predicted outcome of trees. The key concept is bootstrap sampling, which means the model can select useful feature by itself. It is based on ensemble learning framework called bagging. Since it will randomly sample and based on many decision trees models, it is given name Random Forest. LSTM is a kind of recurrent neural network (RNN) architecture. When dealing with sequential data, LSTMs operate especially well in tasks like time series prediction. By keeping a memory cell state and controlling the information flow using different gates (forget, input, and output), they can learn long-term dependencies. XGBoost makes use of a gradient boosting framework, which iteratively constructs a sequence of decision trees with the goal of fixing the mistakes produced by the preceding ones. Because XGBoost is highly adjustable and integrates many regularization algorithms to prevent overfitting, users can fine-tune various parameters to maximize performance for jobs.

2.3. Evaluation Metrics

Several evaluation metrics for quantification are selected. Mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE) and median absolute percentage error (MedAPE) are used. The equations for the metrics are defined as follows:

$$\mathrm{MAE} = \frac{1}{N}\sum_{t=1}^{N}|x_t - \hat{x}_t| \tag{1}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{t=1}^{N}(x_t - \hat{x}_t)^2 \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(x_t - \hat{x}_t)^2} \tag{3}$$

$$\mathrm{MAPE} = \frac{100}{N}\sum_{t=1}^{N}\frac{|x_t - \hat{x}_t|}{|x_t|} \tag{4}$$

$$\text{Median APE} = \text{median}\left(\sum_{t=1}^{N}\frac{|x_t - \hat{x}_t|}{|x_t|}\right) \times 100 \tag{5}$$

3. Results and Discussion

3.1. Model Performance

Table 1 shows two cryptocurrencies performance of 3 different models in 1 day prediction. In 1 day price prediction windows, there is huge difference between MAPE (mean absolute percentage error) and MedAPE (median absolute percentage error). MAPE is bigger than MedAPE. It means that there are some extreme outliers and large error point in prediction result. Except LSTM model in HT prediction has MAPE at 14.8547 and MedAPE at 8.6250, the other models in 1 day prediction all have MAPE within 10 and MedAPE below 5. The best MAE and MedAPE occur in RF model of BNB, have value 0.0375 and 1.4986 respectively. The best MSE and RMSE occur in LSTM model of BNB, have value 0.0045 and 0.0668 respectively. The best MAPE occur in RF model of HT, has value 7.4470. Table 2 lists two cryptocurrencies performance of 3 different models in 3 days prediction. In 3 days price prediction windows, the circumstance of much higher MAPE than MedAPE occurs as in 1 day prediction. The gap between them even bigger than 1 day prediction, while 1 day prediction has average gap between MAPE and MedAPE at 5.51685, 3 days prediction

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has average gap at 8.70855. Additionally, LSTM model in HT prediction has the worst performance comparing to other models in the same prediction windows. The best MAE, MSE, RMSE and MedAPE occur in one model, which is RF model of BNB, have value 0.0522, 0.0125, 0.1119 and 2.1032 separately. Furthermore, the best MAPE is 10.3034 in RF model of HT. Table 3 gives two cryptocurrencies performance of 3 different models in 7 days prediction. The gap between MAPE and MedAPE have average 8.0767, maximum 8.9201 and minimum 7.0138. The best MAE, MSE and RMSE appear in RF model of BNB, with value 0.0502, 0.0075 and 0.0866. The best MAPE and MedAPE appear in XGBoost of BNB. Table 4 shows two cryptocurrencies performance of 3 different models in 30 days prediction. The gap between MAPE and MedAPE have average 8.1119, maximum 16.261 and minimum 5.8253. The best MAE, MSE, RMSE and MAPE appear in XGBoost of BNB, with value 0.0391, 0.0050, 0.0709 and 8.4544. The best MedAPE is 1.7953 in RF model of BNB.

Table 1: 1 day prediction.

		MAE	MSE	RMSE	MAPE	MedAPE
BNB	RF	0.0375	0.0097	0.0983	7.5550	1.4986
	LSTM	0.0477	0.0045	0.0668	9.2266	4.5003
	XGBoost	0.0401	0.0081	0.0901	8.5495	2.0475
HT	RF	0.0484	0.0167	0.1294	7.4470	2.7951
	LSTM	0.0688	0.0108	0.1038	14.8547	8.6250
	XGBoost	0.0562	0.0203	0.1424	8.0956	3.1608

Table 2: 3 days prediction.

		MAE	MSE	RMSE	MAPE	MedAPE
BNB	RF	0.0522	0.0125	0.1119	13.2490	2.1032
	LSTM	0.0790	0.0146	0.1209	13.3660	6.8584
	XGBoost	0.0541	0.0139	0.1181	13.6546	2.5230
HT	RF	0.0626	0.0276	0.1663	10.3034	4.3690
	LSTM	0.1292	0.0608	0.2465	25.5248	13.9880
	XGBoost	0.0682	0.0267	0.1636	11.3300	5.3349

Table 3: 7 days prediction.

		MAE	MSE	RMSE	MAPE	MedAPE
BNB	RF	0.0502	0.0075	0.0866	12.0026	3.0825
	LSTM	0.0746	0.0137	0.1172	13.6052	5.4588
	XGBoost	0.0513	0.0089	0.0944	10.7127	2.6898
HT	RF	0.0722	0.0245	0.1566	13.9384	5.4820
	LSTM	0.1068	0.0225	0.1501	19.9678	12.9540
	XGBoost	0.0727	0.0281	0.1676	13.2580	5.3575

Table 4: 30 days prediction.

		MAE	MSE	RMSE	MAPE	MedAPE
BNB	RF	0.0419	0.0054	0.0732	9.0872	1.7953
	LSTM	0.0778	0.0138	0.1177	22.5940	6.3330
	XGBoost	0.0391	0.0050	0.0709	8.4544	1.9605
HT	RF	0.0669	0.0218	0.1479	12.7072	5.9174
	LSTM	0.1123	0.0351	0.1874	18.6770	12.6673
	XGBoost	0.0612	0.0151	0.1230	10.9891	5.1638

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To better comparison, the results of different models are separated summarized. Table 5 illustrates evaluation metrics of RF model. The best MAE and MedAPE belong to 1 day prediction of BNB, which are 0.0375 and 1.4986. The best MSE and RMSE belong to 30 days prediction of BNB. The best MAPE belongs to 1 day prediction of HT, which is 7.4470. The gap between MAPE and MedAPE have average 7.4058, maximum 11.1458 and minimum 4.6519. Table 6 shows evaluation metrics of LSTM model. The best model prediction is 1 day prediction of BNB, with best MAE, MSE, RMSE, MAPE and MedAPE. The gap between MAPE and MedAPE have average 8.3039, maximum 16.2610 and minimum 4.7263. Table 7 shows evaluation metrics of XGBoost model. The best MAE, MSE, RMSE and MedAPE belong to 30 days prediction model of BNB, with value 0.0391, 0.0050, 0.0709 and 1.9605. The best MAPE is 8.0956, belongs to 1 day prediction of HT. The gap between MAPE and MedAPE have average 7.1008, maximum 11.1316 and minimum 4.9348.

Table 5: Random Forest Performance

		MAE	MSE	RMSE	MAPE	MedAPE
BNB	1 DAY	0.0375	0.0097	0.0983	7.5550	1.4986
	3 DAYS	0.0522	0.0125	0.1119	13.2490	2.1032
	7 DAYS	0.0502	0.0075	0.0866	12.0026	3.0825
	30 DAYS	0.0419	0.0054	0.0732	9.0872	1.7953
HT	1 DAY	0.0484	0.0167	0.1294	7.4470	2.7951
	3 DAYS	0.0626	0.0276	0.1663	10.3034	4.3690
	7 DAYS	0.0722	0.0245	0.1566	13.9384	5.4820
	30 DAYS	0.0669	0.0218	0.1479	12.7072	5.9174

Table 6: LSTM Performance

		MAE	MSE	RMSE	MAPE	MedAPE
BNB	1 DAY	0.0477	0.0045	0.0668	9.2266	4.5003
	3 DAYS	0.0790	0.0146	0.1209	13.366	6.8584
	7 DAYS	0.0746	0.0137	0.1172	13.6052	5.4588
	30 DAYS	0.0778	0.0138	0.1177	22.594	6.3330
HT	1 DAY	0.0688	0.0108	0.1038	14.8547	8.6250
	3 DAYS	0.1292	0.0608	0.2465	25.5248	13.9880
	7 DAYS	0.1068	0.0225	0.1501	19.9678	12.9540
	30 DAYS	0.1123	0.0351	0.1874	18.677	12.6673

Table 7: XGBoost Performance

		MAE	MSE	RMSE	MAPE	MedAPE
BNB	1 DAY	0.0401	0.0081	0.0901	8.5495	2.0475
	3 DAYS	0.0541	0.0139	0.1181	13.6546	2.5230
	7 DAYS	0.0513	0.0089	0.0944	10.7127	2.6898
	30 DAYS	0.0391	0.0050	0.0709	8.4544	1.9605
HT	1 DAY	0.0562	0.0203	0.1424	8.0956	3.1608
	3 DAYS	0.0682	0.0267	0.1636	11.3300	5.3349
	7 DAYS	0.0727	0.0281	0.1676	13.2580	5.3575
	30 DAYS	0.0612	0.0151	0.1230	10.9891	5.1638

3.2. Comparison

Prediction window comparison is divided into two parts, which are the performance in dealing with outliers and average performance. Fig. 3 and Fig. 4 correspond to these two parts and will be discussed and give explanation as follow. Fig. 3 shows the difference between MAPE (Mean APE) and Median APE, with mean difference, max difference and min difference comparing to the prediction windows. The bigger the difference is, the more extreme outliers and large error point in prediction result. 1 day prediction has the lowest gap out of all prediction windows, with the smallest mean, max and min difference value. 30 days prediction window is the most unstable model, with the largest gap between the max difference and min difference, which the gap is 10.43. Fig. 4 presents the average MSE among 3 ML models and 2 cryptocurrencies in the same prediction window. According to the analysis, 1 day prediction window outperforms all prediction windows with the average MSE 0.0117. And the worst prediction window is 3 days prediction window.

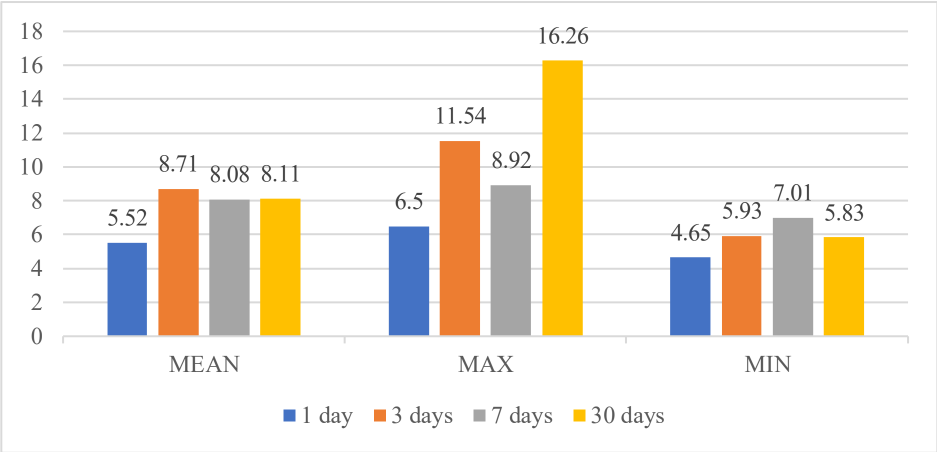

Figure 3: APE Difference of prediction windows (Photo/Picture credit: Original).

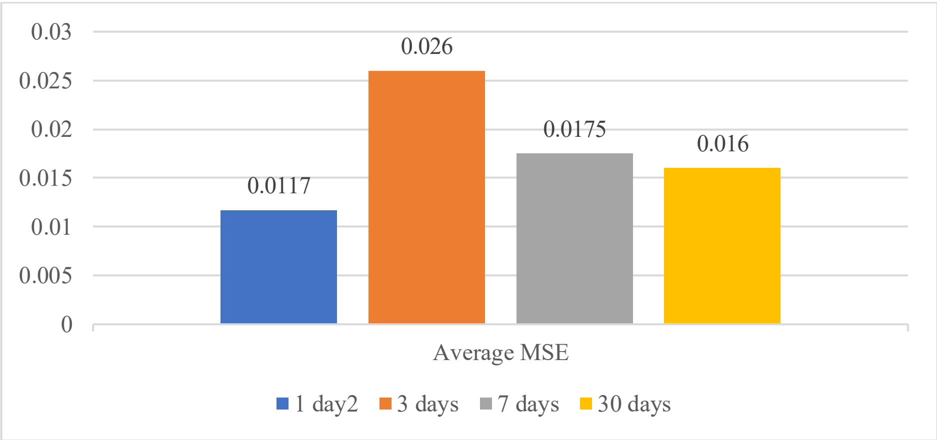

Figure 4: Average MSE (Photo/Picture credit: Original).

For model comparison, it is divided into two parts, which are the performance in dealing with outliers and average performance. Fig. 5 and Fig. 6 correspond to these two parts and will be discussed and give explanation as follow. Fig. 5 illustrates the difference between MAPE (Mean APE) and Median APE, with mean difference, max difference and min difference comparing to the ML models. LSTM is the most unstable model since it has the biggest mean of the gap and with the largest gap between the max difference and min difference. RF and XGBoost have similar performance when dealing with extreme outliers. Fig. 6 demonstrates the average MSE among 4 prediction windows and 2 cryptocurrencies in the same ML models. As result, LSTM is the worst model while RF and XGBoost have almost equivalent performance.

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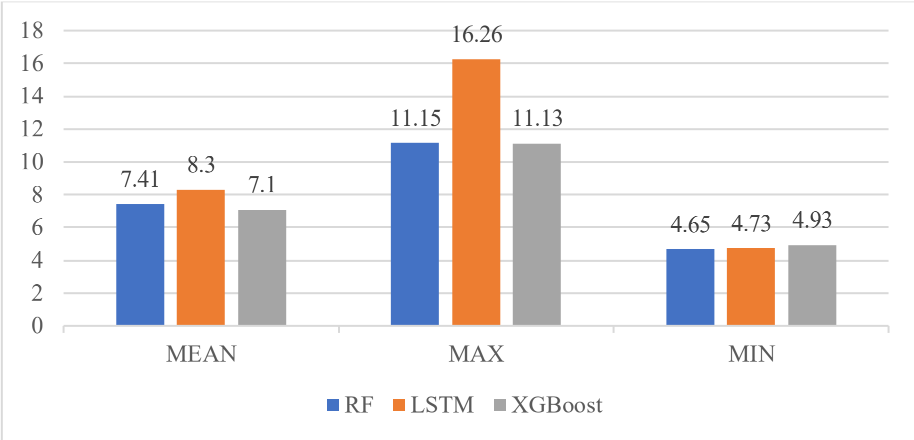

Figure 5: APE Difference of ML models (Photo/Picture credit: Original).

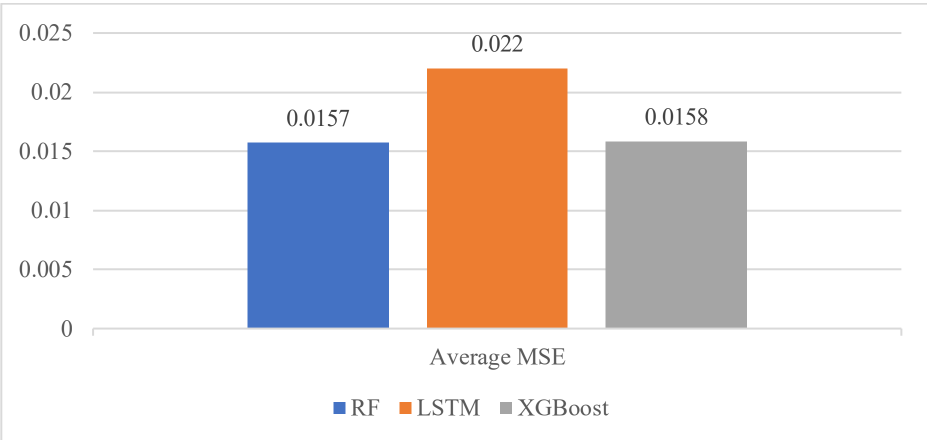

Figure 6: Average MSE of ML models (Photo/Picture credit: Original).

4. Limitations and Prospects

The research is focus on the price prediction of cryptocurrencies related to Defi ecosystem and the crypto are relatively niche. The performance is not very well since the best MAPE in all models of all prediction windows is about 7.4470. There is big gap between the MAPE and Median APE, which mean models can not to deal with the outliers very properly and make large error point in prediction result. Moreover, feature selection is based on the research that concentrate on popular and high market cap cryptocurrencies, e.g., Bitcoin (BTC) and Ethereum (ETH). However, there are more information about relationship between Defi market and tokens is not dug out. Since feature selection is crucial for model training and model performance, finding out some features that deep bond to the tokens and Defi market and can really represent the characteristic of the tokens but not suit for all cryptocurrencies is essential. Additionally, ensemble technique and hybrid model are absent. Therefore, author can just give conclusion of the single model performance.

Cryptocurrency is fast-paced development financial market nowadays. Technology innovation and ambitious vision of establish decentralized financial market accelerate expansion of cryptocurrency market. People try to build more application on it and DeFi ecosystem comes out. Nobody can say which cryptocurrencies will dominate the market, since the decentralized system still in the starting period. In future work, more cryptocurrencies that are not so popular yet should be explore more to fill the gap in the research field of cryptocurrencies. More characteristic of fresh and niche cryptocurrencies should be investigated to be more suitable features of model training. For instance, in this paper, two tokens chosen have their background based on the crypto exchange platform and Defi applications. There are more features can be focus on base on the platform, e.g., user engagement and user count, or token adoption within the platform, or the development of exchange platform. Additionally, there are also some features can be explored base on DeFi ecosystem, such as the features could show market demand and the growth of the specialty market. The machine learning model refinement and integration should be tackled in future. Since fluctuations of price of cryptocurrencies exist, capability of dealing with extreme price variance is vital. In this study, models have poor performance when handling with outliers. In forthcoming endeavors, more ensemble technique and hybrid model should be explored of this new cryptocurrency price prediction field.

5. Conclusion

To sum up, two tokens of niche cryptocurrency market, Biance Boin (BNB) and Huobi Token (HT), are used as targets for price prediction based on machine learning models. Four groups of features are chosen, which are technical indicators, other crypto, macroeconomics and traditional commodities. Three ML models are selected, which are Random Forest (RF), Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost). Four prediction windows are used, which are 1,3,7 and 30 days. Performance comparison is divided into two parts, for prediction window comparison and model comparison. Each of comparison is separated into two sections, which are using difference between MAPE and Median APE to evaluate capability of dealing with outliers and using average MSE of all model performance to evaluate ability of average performance. In prediction window comparison, 1 day prediction has the lowest APE gap out of all prediction windows, with the smallest mean, max and min difference value. 30 days prediction window is the most unstable model, with the largest gap between the max difference and min difference, which the gap is 10.43. Furthermore, in average performance evaluation, 1 day prediction window outperforms all prediction windows with the average MSE 0.0117. The worst prediction window is 3 days prediction window. In model comparison, LSTM is the most unstable model since it has the biggest mean of the gap and with the largest gap between the max difference and min difference. RF and XGBoost have similar performance when dealing with extreme outliers. In addition, comparing average MSE for average performance, LSTM is the worst model while RF and XGBoost have almost equivalent performance. In future work, more cryptocurrencies of niche market should be explored. Features that are more suitable for tokens of Defi market can be further investigation. Hybrid approaches and ensemble technique can be applied and adopted to improve price prediction performance.

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