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Most Volatile Crypto currency Price Forecasting

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Abstract: *Cryptocurrency has been considered an extremely speculative investment by people around the globe. This project aims to comprehend the historical data of Bitcoin and derive analysis from it to reduce the gap of understanding between the market behaviour and the investor. Cryptocurrency data constitutes a bunch of statistical representations which are tough to understand by an ordinary person who wishes to step into market investments, this project intends for at reducing the gap of knowledge. This study aspires to explain the market scenario of the future by aiding it with statistical conclusions.*

Background*: Cryptocurrency's are very unpredictable, any geopolitical change can impact the share trend of cryptocurrency in the market, and recently we have seen how Covid-19 has impacted the cryptocurrency prices, which is why on financial data doing a reliable trend analysis is very difficult. The most effective way to solve this kind of issue is with the help of Machine learning and deep learning. In the tutorial, we will be solving this problem with AR, MA, ARMA, and SARIMA Model. A popular and widely used statistical method for time series forecasting is the ARIM Model. It is one of the most popular models to predict linear time series data.*

Materials and Methods*: The most effective way to analysis with the help of Machine learning and deep learning. In the tutorial, we will be solving this problem with AR, MA, ARMA, and SARIMA Model. A popular and widely used statistical method for time series forecasting is the ARIM Model. It is one of the most popular models to predict linear time series data. This model has been used extensively in the field of finance and economics as it is known to be efficient, and has a strong potential for short- term share market prediction. Expanding smoothing and forecasting and provide complementary approaches to the problem. While expanding smoothing models are based on a description of the trend and seasonality in the data, ARIMA models aim to describe the auto-correlation in the data.*

Results*: There is a positive correlation between ETH-USD and BTC-USD. The prices moment of bitcoin and Ethereum as much similar to each other. As the price of bitcoin rises the price of Ethereum also increases simultaneously.Best Fitted model is SARIMAX (1, 1, 0) x (0, 1, 1, 12) with smallest AIC value. And the equation is* $\Phi 1 (\beta) (1- \beta 12) (1- \beta)' Yt = \Phi 1(\beta 12) Zt$. *From our analysis we may say that price of bitcoin goes up with time. Approximated price target for bitcoin for end of 2024 is more than at most 1.4 Lakh USD. After doing LSTM we got to know that model is giving value 0.66 i.e. 66% model's variance that is explained by our model's independent*
features.

Key Word*:Cryptocurrency, Bitcoin, Time Series, Stochastic, Prediction, Trend, etc.*

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I. Introduction

A prediction method is processing that values, data for predict future based values on past and present data. These historical data points are take-out and prepared trying to predict future values for selected variable of the dataset. In this project application we will focus on quantitative our variable forecasting involving. to forecast statistical principals' analysis and advanced Concepts applied to data a given historical data.

During market history there have been a continuous interest trying to analyses its liability, behavior and random reactions. This continuous concern to understand what happens before it really happens motivate us to continue with this study. Some great market traders and economists says that is almost impossible to predict stock returns or prices referring to, independence between each other, the past movements or trends cannot be used to predict future values, explained by random walk theory, skewness, kurtosis and big random component.

II. Material and Methods

This prospective comparative study was carried out on price of Binance, Ethereum, Ripple and Bitcoin
Study Design: Prospective open label observational study, time series analysis, stochastics and data mining technique

Study Location: Data source is secondary.

Study Duration: June 2022.

Sample size: Total 4857376 observations.

Sample size calculation: There are 4857376 observations in data set starts from the since bitcoin created. Every minute price traded bitcoin taken in consideration since bitcoin created.

Subjects & selection method: Details cryptocurrency analysis with the higher market cap and trading volume.

Inclusion criteria:
1. Cryptocurrency with higher market cap.
2. Cryptocurrency with higher trading volume.
3.

Exclusion criteria:
1. Cryptocurrency with less market cap.
2. Cryptocurrency with less trading volume.
3. Less popular cryptocurrency's

Procedure methodology:
Time series approach:

A time series is a sequence of observations recorded over a distinct period. Time series forecasting obtains data scrutinizing historical values and associated patterns to anticipate forthcoming activity. Most frequently, this is associated with trend analysis, cyclical fluctuation analysis, and issues of seasonality. As with all forecasting methods, accomplishment is not guaranteed.

Market volatility, Daily returns, cumulative returns, Correlations between numerous cryptocurrencies, Sharpe Ratio of the cryptocurrency, CAGR value, and Simple Moving Average are some significant statistical terms to comprehend the threat of the investment in the cryptocurrency. For the vision of the future behavior of cryptocurrency work on TIME SERIES analysis. We will interpret this issue with the help of statistical tools.

Data mining Approach: -
Training and Test Sets: Splitting Data
The idea of dividing your data set into two subsets:
1. training set—a subset to train a model.
2. test set—a subset to test the trained model.

Make sure that your test set meets the following two conditions:
1. Is large enough to yield statistically meaningful results.
2. Is representative of the data set as a whole. In other words, don't pick a test set with differentcharacteristics than the training set.

Assuming that your test set meets the preceding two conditions, your goal is to create a model that generalizes well to new data. Our test set serves as a proxy for new data. For example, consider the following figure. Notice that the model learned for the training data is very simple. This model doesn't do a perfect job a few predictions are wrong. However, this model does about as well on the test data as it does on the training data. In other words, this simple model does not over fit the training data.

Introduction to Long Short-Term Memory(LSTM): -

Long Short-Term Memory is a kind of recurrent neural network. In RNN output from the last step is fed as input in the current step. LSTM was designed by Hochreiter & Schmidhuber. It tackled the problem of long-term dependencies of RNN in which the RNN cannot predict the word stored in the long-term memory but can give more accurate predictions from the recent information. As the gap length increases RNN does not give an efficient performance. LSTM can by default retain the information for a long period of time. It is used for processing, predicting, and classifying on the basis of time-series data.

Stochastic Process: -

Block chain technology has been attracting much attention from both academia and industry. It brings many benefits to various requests like Internet of Things. However, there are dangerous issues to be spoken before its widespread deployment, such as transaction efficiency, bandwidth blockage, and security. Practices are being explored to tackle these questions. Stochastic modeling, as one of these techniques, has been applied to analyze a variation of block chain characteristics, but there is a nonexistence of a wide-ranging survey on it. In this assessment, we goal to fill the gap and criticism the stochastic models projected to address common issues in block chain. Firstly, this paper affords the basic acquaintance of block chain technology and stochastic models. Then, allowing to different objects, the stochastic models for block chain examination are divided into network-oriented and application-oriented (mainly refer to cryptocurrency).

Statistical analysis

Data was analyzed using Python .Analysis starts with a data cleaning and processingin that we clear the data and make it good fit for a analysis 1st up all we calculate the adj close price to visualization data and then we calculate percentage return for a measure volatility in the particular data's in pairs. From Histogram of returns clearly sees that our data follows normal distributions. After finding correlation between all pairs sees that the moment of a Ethereum and Bitcoin are co related and there price moment are much similar to each other. From above analysis see that bitcoin is almost volatile cryptocurrency and then we goes for further analysis. For that analysis we use time series analysis, data mining technique which is LSTM (LONG SHORT TEM MEMORY) and stochastic analysis.

III. Result

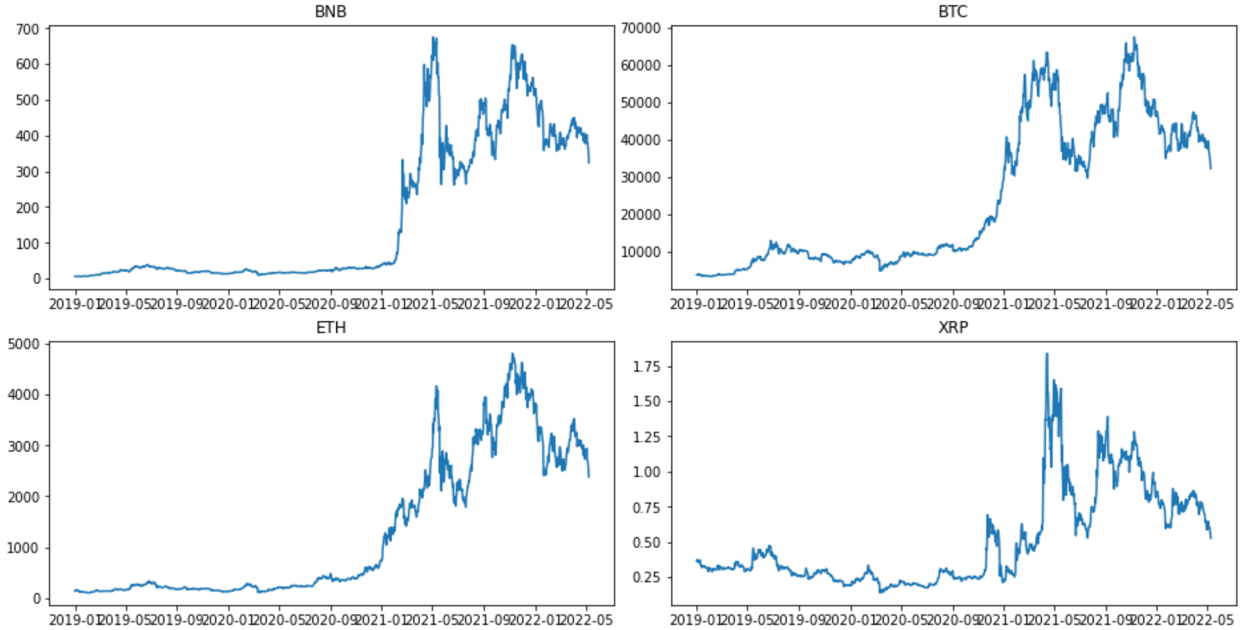
ACryptocurrency Data: -

	Adj Close				Close				High		Low		Open				Volume			
	BNB-USD	BTC-USD	ETH-USD	XRP-USD	BNB-USD	BTC-USD	ETH-USD	XRP-USD	BNB-USD	BTC-USD	ETH-USD	XRP-USD	BNB-USD	BTC-USD	ETH-USD	XRP-USD	BNB-USD	BTC-USD	ETH-USD	XRP-USD
Date																				
01-01-2019	6.07527	3843.52	140.819	0.36477	6.07527	3843.52	140.819	0.36477	6.19193	3850.91	132.651	0.3504	6.19143	3746.71	133.418	0.35251	2.4E+07	4.3E+09	2.3E+09	4.5E+08
02-01-2019	6.18861	3943.41	155.048	0.37524	6.18861	3943.41	155.048	0.37524	6.20787	3947.98	140.651	0.35957	6.09147	3849.22	141.52	0.36568	3E+07	5.2E+09	3.3E+09	5.4E+08
03-01-2019	5.90354	3836.74	149.135	0.36022	5.90354	3836.74	149.135	0.36022	6.17512	3935.69	147.198	0.35768	6.17191	3931.05	155.196	0.37451	2.3E+07	4.5E+09	2.7E+09	4.4E+08
04-01-2019	6.06514	3857.72	154.582	0.35675	6.06514	3857.72	154.582	0.35675	6.0659	3865.93	147.907	0.35279	5.89505	3832.04	148.913	0.35975	2.9E+07	4.8E+09	3.1E+09	4.5E+08
05-01-2019	6.06554	3845.19	155.639	0.35528	6.06554	3845.19	155.639	0.35528	6.20438	3904.9	154.337	0.35399	6.05566	3851.97	154.337	0.35635	3E+07	5.1E+09	3.3E+09	4.5E+08

For analysis we only take adj close prices.

Date	BNB-USD	BTC-USD	ETH-USD	XRP-USD
01-01-2019	6.075273	3843.52002	140.819412	0.364771
02-01-2019	6.188613	3943.409424	155.047684	0.375243
03-01-2019	5.903535	3836.741211	149.13501	0.360224
04-01-2019	6.065138	3857.717529	154.58194	0.356747
05-01-2019	6.065543	3845.19458	155.638596	0.35527

Date Visualization: -
plotting the adjusted closing price.



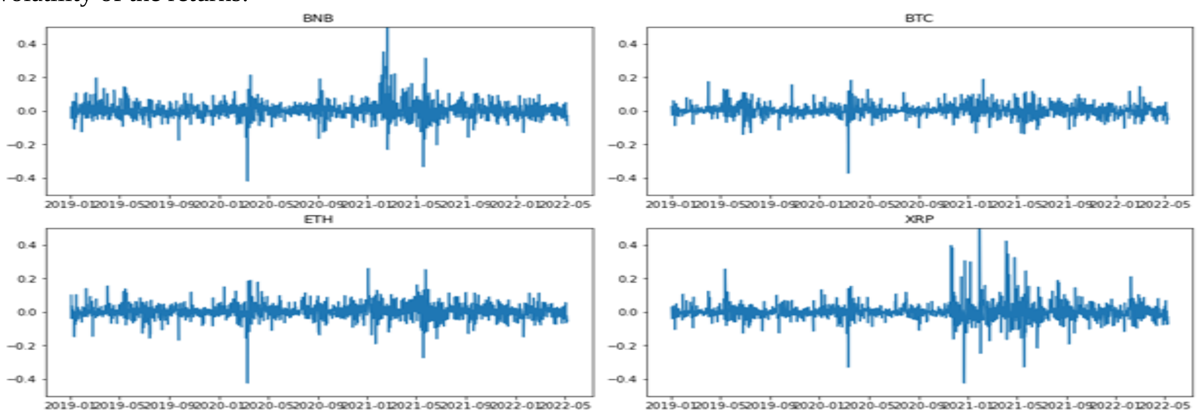
Percentage Return: -

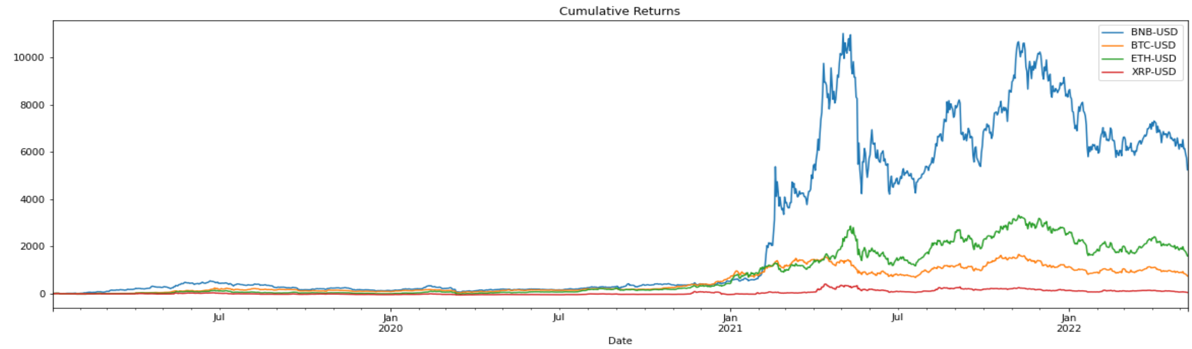
	BNB-USD	BTC-USD	ETH-USD	XRP-USD
Date				
2019-01-02	0.018656	0.025989	0.101039	0.028708
2019-01-03	-0.046065	-0.027050	-0.038135	-0.040025
2019-01-04	0.027374	0.005467	0.036523	-0.009652
2019-01-05	0.000067	-0.003246	0.006836	-0.004126
2019-01-06	0.054478	0.060189	0.013542	0.036929

standard deviation of the returns: -

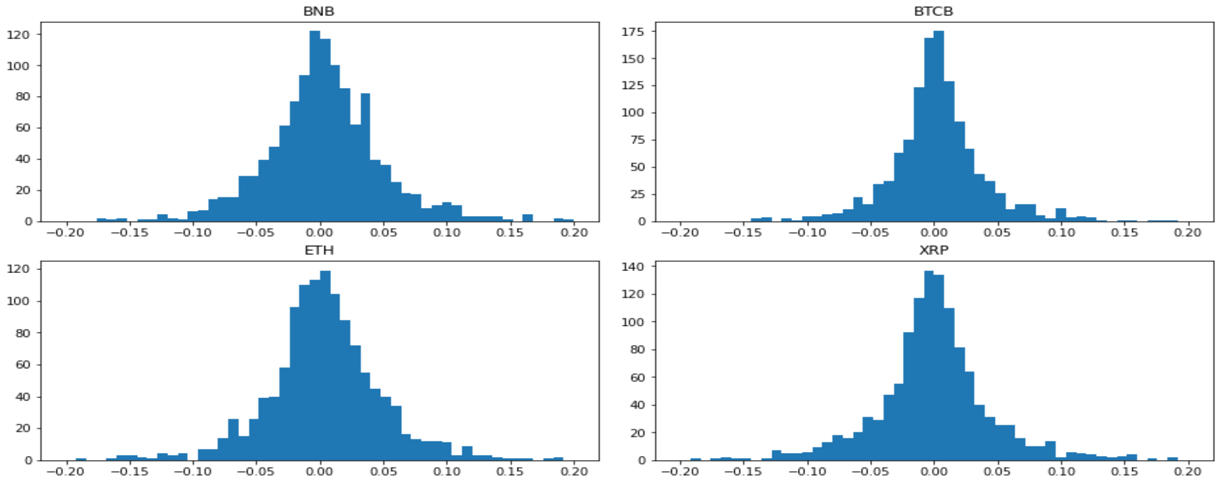
BNB	USD 0.056322
BTC	USD 0.038092
ETH	USD 0.048278
XRP	USD 0.060168

volatility of the returns: -





Histogram of returns: -



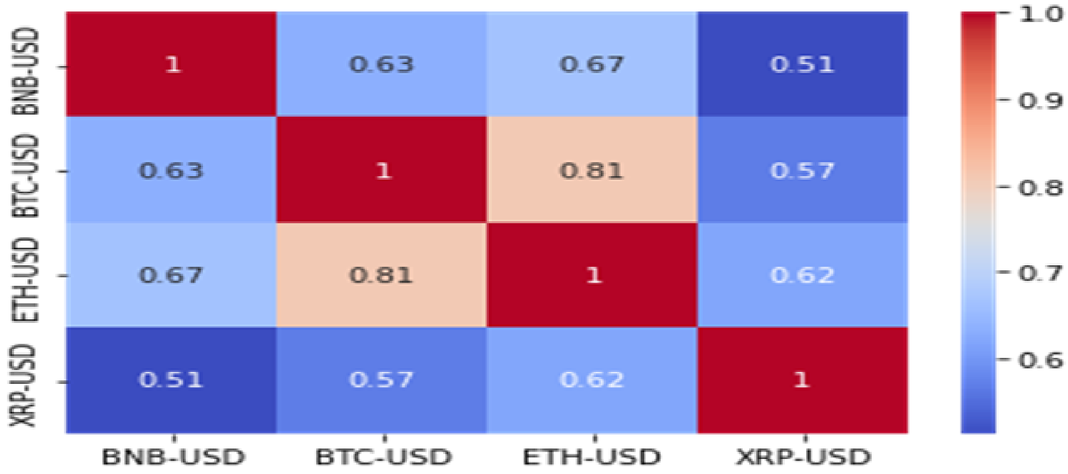
From above chart we can say that our data follows normality.

Cumulative return series: -

	BNB-USD	BTC-USD	ETH-USD	XRP-USD
Date				
2019-01-02	1.865594	2.598904	10.103913	2.870842
2019-01-03	-2.826838	-0.176370	5.905150	-1.246535
2019-01-04	-0.166827	0.369388	9.773175	-2.199738
2019-01-05	-0.160155	0.043568	10.523537	-2.603278
2019-01-06	5.278872	6.065080	12.020209	0.993498

Correlations between Cryptocurrencies: -

	BNB-USD	BTC-USD	ETH-USD	XRP-USD
BNB-USD	1.000000	0.633222	0.666822	0.513443
BTC-USD	0.633222	1.000000	0.808264	0.570435
ETH-USD	0.666822	0.808264	1.000000	0.621571
XRP-USD	0.513443	0.570435	0.621571	1.000000



There is a positive correlation between ETH-USD and BTC-USD. The prices moment of bitcoin and Ethereum as much similar to each other. As the price of bitcoin rises the price of Ethereum also increases simultaneously.

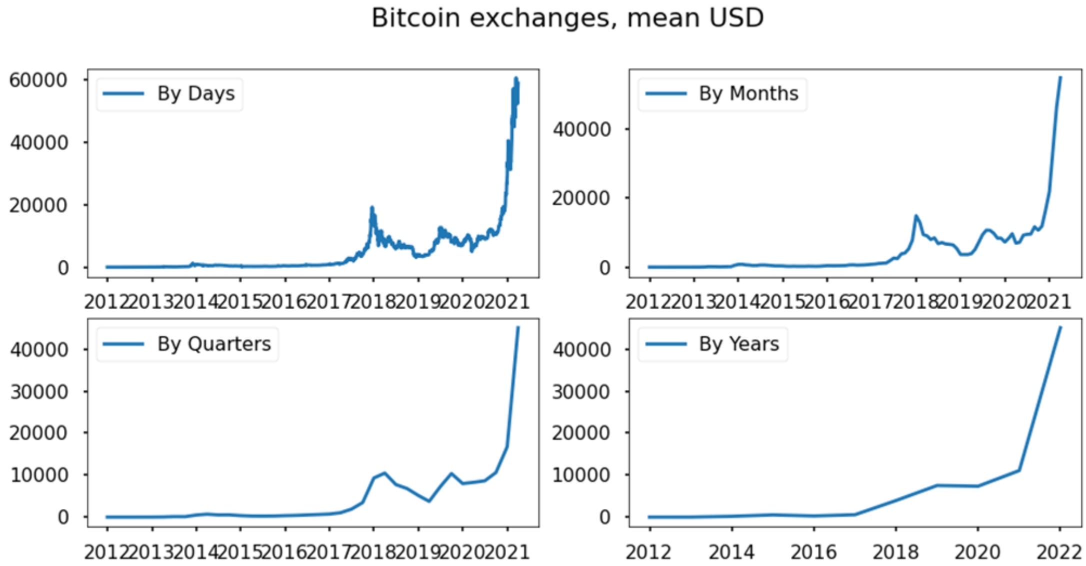
STUDY OF BITCOIN: -

Bitcoin is the most volatile cryptocurrency, that is the only reason we have considered bitcoin into study. Bitcoin effects the market at the highest level, may it be positive or negative.

Data Set: - There are 4857376 observations in data set starts from the since bitcoin created. Every minute value or price traded bitcoin taken in consideration since bitcoin created.

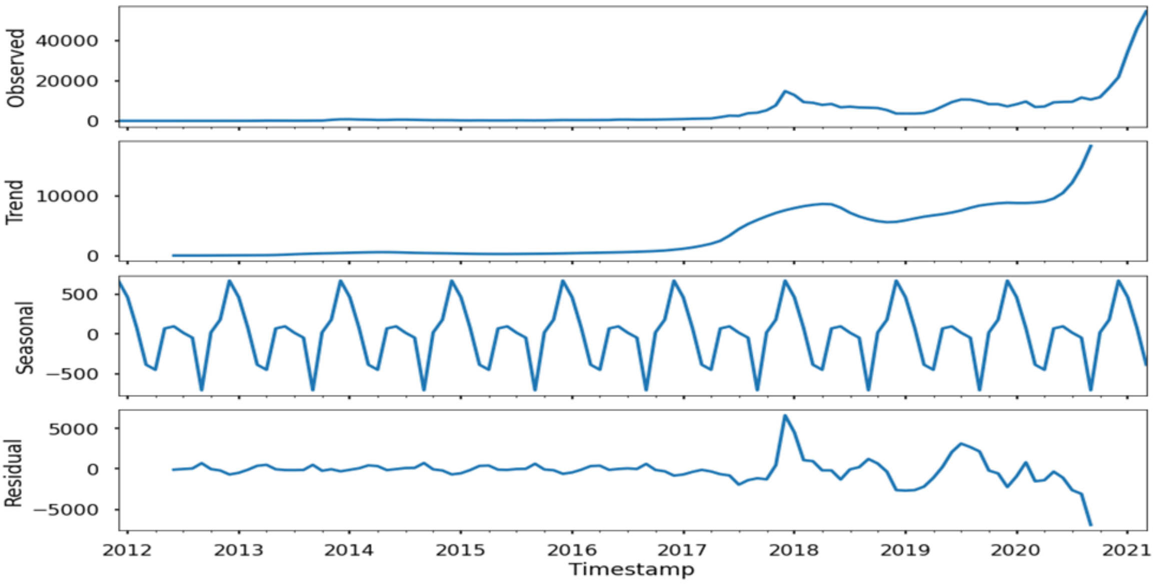
Date	Open	High	Low	Close	Adj Close	Volume
01-10-2014	387.427	411.698	289.296	338.321	338.321	902994450
01-11-2014	338.65	457.093	320.626	378.047	378.047	659733360
01-12-2014	378.249	384.038	304.232	320.193	320.193	553102310
01-01-2015	320.435	320.435	171.51	217.464	217.464	1098811912
01-02-2015	216.867	265.611	212.015	254.263	254.263	711518700
01-03-2015	254.283	300.044	236.515	244.224	244.224	959098300
01-04-2015	244.223	261.798	214.874	236.145	236.145	672338700

Date Visualization: -



Bitcoin price by days, by months, by quarters, by years.

Graphical Representations of Time Series: -



Here we can see that some seasonal component present in the data. The price of bitcoin is positively trend with time.

Decomposition: -

Seasonal Differentiation: -

H0: Time series is stationary
Vs
H1: Time series is non-stationary

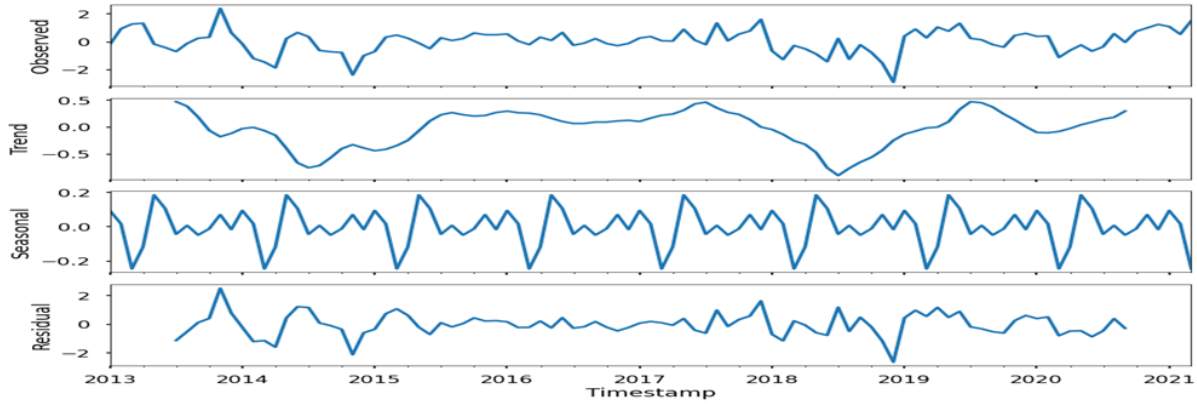
Here, P-value is p =0.0444282
Here, we can see that the p-value for time series is less than 0.05, and we can say we may accept the null hypothesis and the time series is stationary.

Regular Differentiation, STL-Decomposition: -

H0: Time series is stationary
Vs
H1: Time series is non-stationary

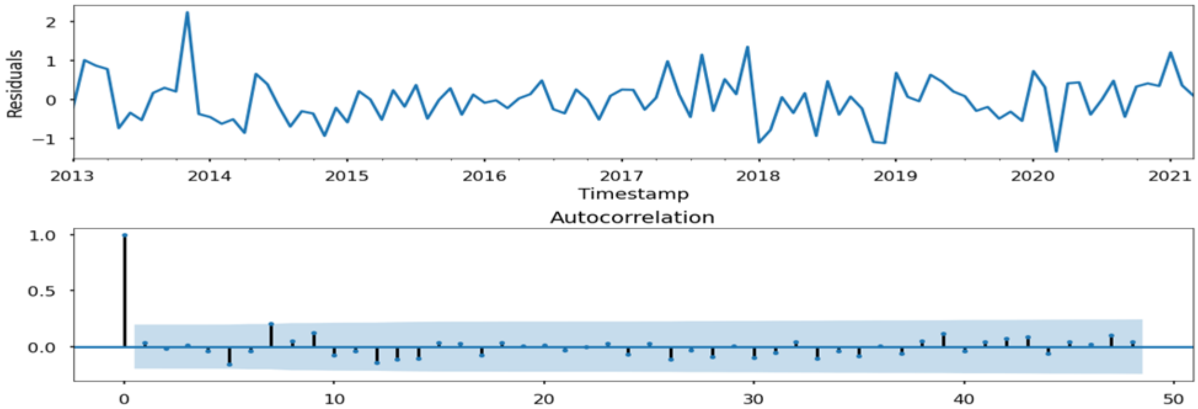
p-value is 0.000024,So we can see that the p-value for time series is less than 0.05, and we can say we may accept the null hypothesis and the time series is stationary.

Graphical Representations of stationary Time Series: -



Here we can see that the data we are using is now stationary because the price of bitcoin is does not integrated positively with time. It means that the statistical properties of a process generating a time series does not change over the time.

Acf-Pacf Graph: -



Here we observed the lag remain in between reference lines so may we conclude that process is stationary.

Now we able to fit Time Series Model: -

Best fitted model: -

AIC	Parameters
173.616125	(1, 0, 0, 1)
174.766384	(2, 0, 1, 1)
175.546901	(1, 1, 0, 1)
175.55421	(2, 0, 0, 1)
175.58886	(0, 1, 0, 1)

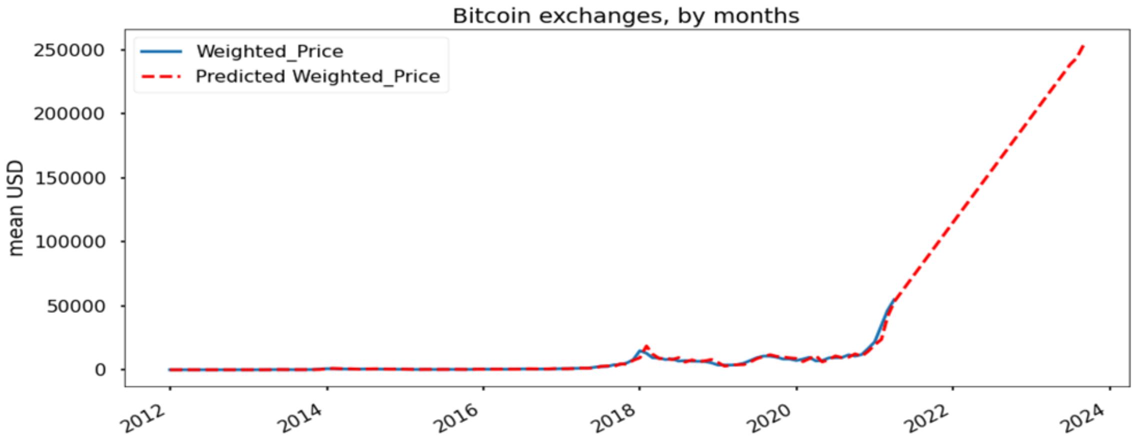
Here We accept model with less AIC which is 173.616125

Best Model Result

Dep. Variable:	Weighted_Price_box	No. Observations:	
Model:	**SARIMAX (1, 1, 0) x (0, 1, 1, 12)**	Log Likelihood	-83.808
Date:	Thu, 12 May 2022	AIC	173.616
Time:	02:57:34	BIC	181.401
Sample:	12-31-2011	HQIC	176.766
	- 03-31-2021		
Ljung-Box (Q):	28.06	Jarque-Bera (JB):	3.59
Prob (Q):	0.92	Prob (JB):	0.17
Heteroskedasticity (H):	1.16	Skew:	0.29
Prob (H) (two-sided):	0.68	Kurtosis:	3.73

Here Best Fitted model is SARIMAX (1, 1, 0) x (0, 1, 1, 12) with smallest AIC value. And the equation is Φ1 (β) (1- β12) (1- β) ' Yt = Φ1(β12) Zt.

Bitcoin Price Prediction Graph for Next 2 Year: -

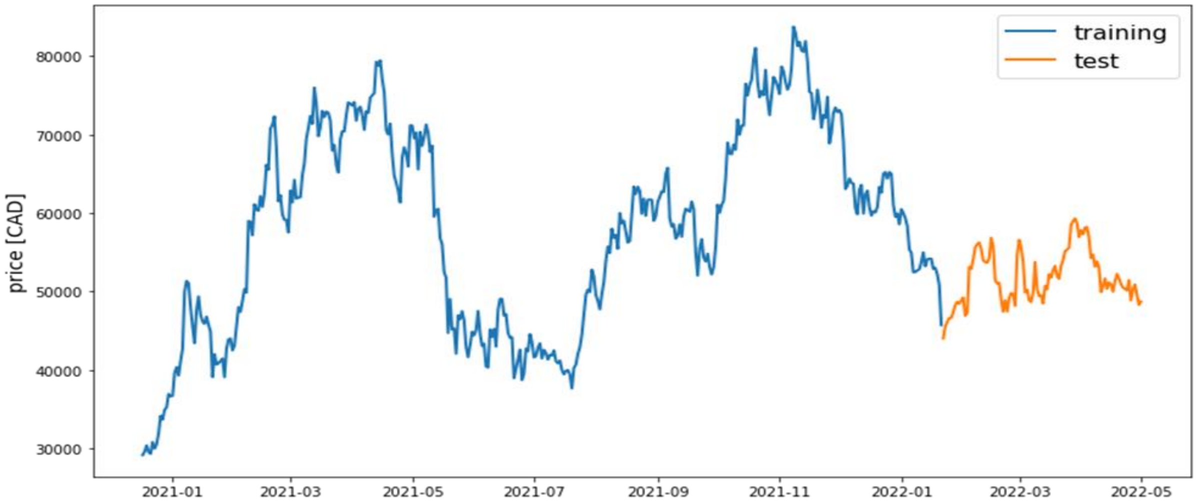


Data Mining Approach: -
Data set divide into two subsets:

- Training set—a subset to train a model.
- Test set—a subset to test the trained model.

You could imagine slicing the single data set as follows:

Graphical Representation of Training and Test Sets: -



Above graph shows that in our model we use data for training and testing. The blue line shows training data and orange line shows test data.

Result of last model: -

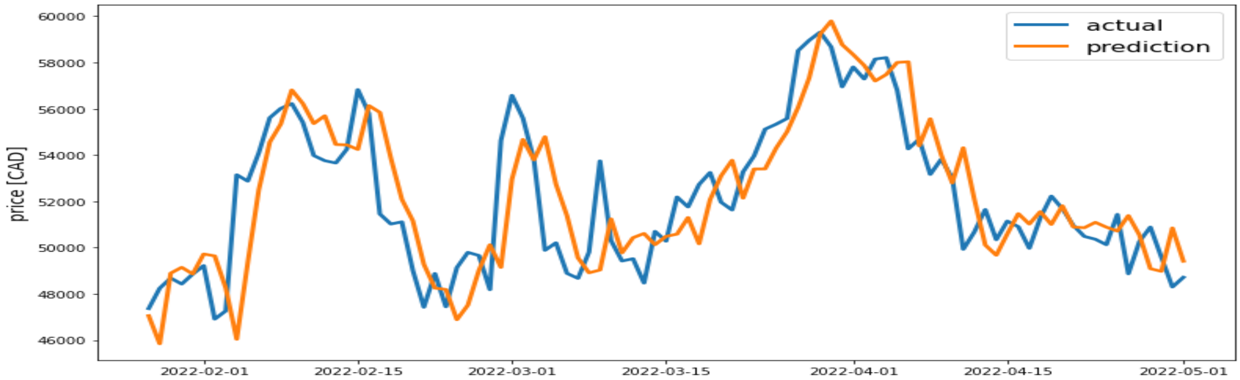
Epoch 1/20
13/13 [==============================] - 4s 50ms/step - loss: 0.0097 - val_loss: 0.0035
Epoch 2/20
13/13 [==============================] - 0s 9ms/step - loss: 0.0103 - val_loss: 0.0033
Epoch 3/20
13/13 [==============================] - 0s 9ms/step - loss: 0.0062 - val_loss: 0.0028
Epoch 4/20
13/13 [==============================] - 0s 14ms/step - loss: 0.0049 - val_loss: 0.0028
Epoch 5/20
13/13 [==============================] - 0s 11ms/step - loss: 0.0052 - val_loss: 0.0024
Epoch 6/20
13/13 [==============================] - 0s 10ms/step - loss: 0.0041 - val_loss: 0.0022
Epoch 7/20
13/13 [==============================] - 0s 10ms/step - loss: 0.0041 - val_loss: 0.0019
Epoch 8/20
13/13 [==============================] - 0s 10ms/step - loss: 0.0044 - val_loss: 0.0018
Epoch 9/20
13/13 [==============================] - 0s 10ms/step - loss: 0.0099 - val_loss: 0.0018
Epoch 10/20
13/13 [==============================] - 0s 10ms/step - loss: 0.0033 - val_loss: 0.0019
Epoch 11/20
13/13 [==============================] - 0s 11ms/step - loss: 0.0041 - val_loss: 0.0019
Epoch 12/20
13/13 [==============================] - 0s 11ms/step - loss: 0.0045 - val_loss: 0.0017
Epoch 13/20
13/13 [==============================] - 0s 11ms/step - loss: 0.0050 - val_loss: 0.0017
Epoch 14/20
13/13 [==============================] - 0s 10ms/step - loss: 0.0052 - val_loss: 0.0016
Epoch 15/20
13/13 [==============================] - 0s 12ms/step - loss: 0.0034 - val_loss: 0.0016
Epoch 16/20
13/13 [==============================] - 0s 12ms/step - loss: 0.0029 - val_loss: 0.0017
Epoch 17/20
13/13 [==============================] - 0s 10ms/step - loss: 0.0043 - val_loss: 0.0016
Epoch 18/20
13/13 [==============================] - 0s 13ms/step - loss: 0.0042 - val_loss: 0.0015

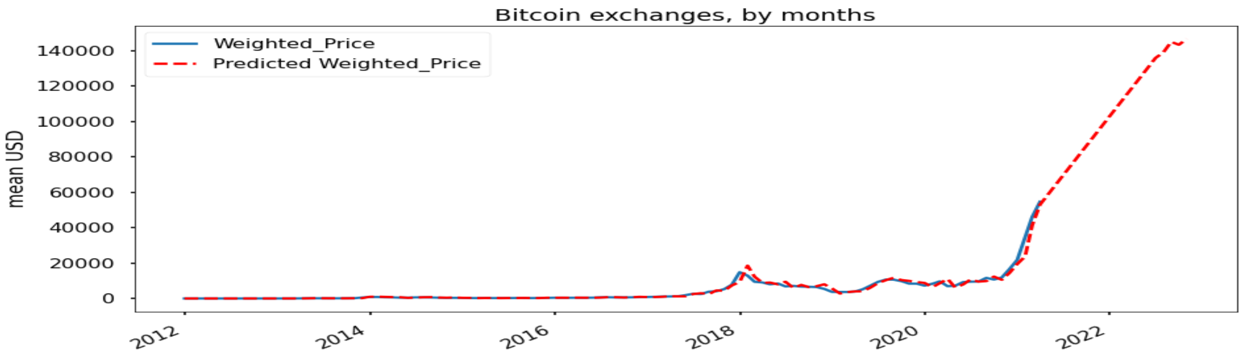
Epoch 19/20
13/13 [==============================] - 0s 11ms/step - loss: 0.0041 - val_loss: 0.0014
Epoch value0
13/13 [==============================] - 0s 11ms/step - loss: 0.0041 - val_loss: 0.0015

Where,
Mean Absolute error= 0.028158176074534216
Mean Squared error= 0.0014910208682400216
R-sq.=0.6604688891522011

After doing LSTM we got to know that model is giving value 0.66 i.e. 66% model's variance that is explained by our model's independent features.

Predictedvalue: -





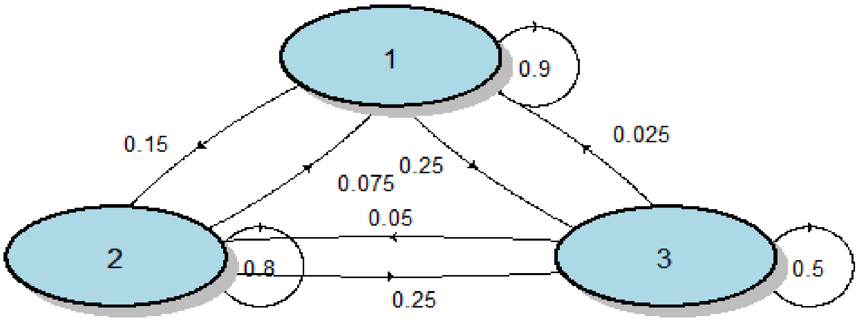
Cryptocurrency Market: -

A 3 - dimensional discrete Markov Chain defined by the following states:
Bull market, Bear market, Stagnate market
The transition matrix (by rows) is defined as follows:

	Bull market	Bear market	Stagnate market
Bull market	0.9	0.075	0.025
Bear market	0.15	0.8	0.05
Stagnate market	0.25	0.25	0.5

A state diagram for a simple example is shown in the figure above, using a directed graph to picture the state transitions. The states represent whether a hypothetical market is exhibiting a bull market, bear market, or stagnant market trend during a given week. According to the figure, a bull week is followed by another bull week 90% of the time, a bear week 7.5% of the time, and a stagnant week the other 2.5% of the time. Labeling the state space {1 = bull, 2 = bear, 3 = stagnant}.

Transition Graph: -



Summary: -

Market Markov chain that is composed by:
Closed classes: Bull market Bear Market Stagnate market
Recurrent classes: {Bull market, Bear market, Stagnate market}
Transient classes: NONE
The Markov chain is irreducible
The absorbing states are: NONE
Steady states: -

	Bull market	**Bear market**	**Stagnate market**
[1]	**0.625**	**0.3125**	**0.0625**

IV. Conclusion

There is a positive correlation between ETH-USD and BTC-USD. The prices moment of bitcoin and Ethereum as much similar to each other. As the price of bitcoin rises the price of Ethereum also increases simultaneously. After doing time series analysis best fitted model is **SARIMAX (1, 1, 0) x (0, 1, 1, 12) with smallest AIC** value. And the equation is $\boldsymbol{\Phi_1 (\beta) (1- \beta^{12)} (1- \beta)' \; Yt = \Phi_1(\beta^{12}) \; Zt.}$ From our analysis we may say that price of bitcoin goes up with time. Approximated price target for bitcoin for end of 2024 is more than at most 1.4 Lakh USD. After doing LSTM we got to know that model is giving value 0.66 i.e. 66% model's variance that is explained by our model's independent features The steady-state probabilities indicate that 62.5% of weeks will be in a bull market, 31.25% Of weeks will be in a bear market and 6.25% of weeks will be stagnant.

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