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Deep Learning Based Adaptive Multimodal System for Bitcoin Price Prediction

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Abstract: Cryptocurrencies are the best example of Blockchain. And the Blockchain is a decentralized network where they are multiple nodes that control the network. Bitcoin established itself as the first decentralised cryptocurrency in 2009. Bitcoin revolutionized the crypto world and all other cryptocurrencies other than bitcoin such as Ethereum, Ripple, etc. are called altcoins. In the crypto market, the price of bitcoin reflects the other cryptocurrencies. Therefore, our intention is to create prediction models which uses deep learning concepts for bitcoin and to forecast its future price.
Keywords: Bitcoin, Price Prediction, Cryptocurrencies, Neural Network

I. INTRODUCTION

Investors and scholars find market price forecasting fascinating and difficult due to its complexity. There are a lot of unknowns and things to think about. The market may be affected by economic conditions and other reasons. [1] As a result of recent political developments, the market has grown not only more competitive but also more diversified. When it comes to the stock market, foreign exchange (FX), and cryptocurrencies, ODO defines cryptocurrency as a digital currency. A cryptocurrency is a form of money that is governed by encryption algorithms. The establishment of money units and the verification of currency transfers, that is not subject to central bank supervision. The prediction of future prices is one of the key objectives of bitcoin analytics. The price dynamics are influenced by a variety of things. The supply-demand relationship, investor appeal, financial and macroeconomic information, technical indicators like difficulty, the number of freshly generated blocks, and so on are the most crucial elements. Social media and search engine trends have a big impact on bitcoin values. In order to forecast the future price of Bitcoin, we are constructing the ARIMA and FBProhpet models in this work. The goal of this research is to create a model of a neural network that can be used to forecast Bitcoin price movement over the long and short terms. This research is inspired by work done in the stock market price prediction field, which achieves higher accuracy than the cryptocurrency price prediction field by predicting the long-term price.

II. LITERATURE REVIEW MATERIALS AND METHODOLOGY

As traders and investors are anxious to know the price movement of bitcoin in the future, bitcoin price detection is one of the most important aspects today. So, there are several models that have been designed to forecast the price of bitcoin in the future.

This study uses data from daily time series, 10-minute intervals, and 10-second intervals to forecast the price of bitcoin. They created three sets of time series data with intervals of 30, 60, and 120 minutes, and then generated three linear models from the datasets using GLM/Random Forest.

The price of Bitcoin is determined by linearly combining these three models. [2] states that the author is investigating efforts made to forecast the American stock market. At last the result he got that the excess return standard deviation was far more than the mean square error of the predicted network. However, the author demonstrates how a number of fundamental financial and economic factors can forecast the result.

With a 55 percent accuracy rate, Reference [4] used SVM and ANN to forecast the price of Bitcoin using data from the Bitcoin blockchain. In order to predict the short-term Bitcoin price, Random Forest, SVM, and Binomial Logistic algorithms are utilised. This research has one flaw, according to [6]: the outcome was not cross checked, therefore it may have overfit the data and one cannot be sure if the model would generalise.

As a result, [6] uses an LSTM network and accomplishes an accuracy rate of 52%. The majority of prior attempts at predicting the price of cryptocurrencies have estimated short-term Bitcoin values with low accuracy and without cross-validation, endangering traders' confidence in the model.

With Multilayer Perceptron having the most accuracy when projecting the next 60-day price change and Recurrent Neural Networks having the best accuracy when forecasting the following 56-day price change, long-term forecasting triumphs over short-term forecasting with accuracy of 81.3 percent, precision of 81 percent, and recall of 94.7 percent, Multilayer Perceptron surpasses Recurrent Neural Networks. The variations in bitcoin prices based on execution orders like purchase or sell were investigated by Tian et al. [1]. Moving average values and regression approaches were discussed. They developed a time series model that projected bitcoin values using a Gaussian time model. They did, however, show that their model works well with time series data. We tested our proposed model based on the current price of bitcoin using a dataset spanning several years.

A. Arima

The autoregressive and moving average models are working together as a single unit to generate the ARIMA model. This model has been widely used and tested for different kinds of time series. Since seasonal time series make up the majority of data from the actual world, modelling of both seasonal and non-seasonal series must be investigated. In ARIMA, we find the difference between time series from one time stamp to another rather than predicting the time series.

Multiplicative model is used to describe the seasonal time series, which is defined as follows: where x is a periodic term,, and B is the difference operator specified as

Since B(Zt) = Zt-1, (1-Bx)D

D stands for the x seasonal difference in Dth.

(1-B) The seasonal moving average model's order is P, the non-seasonal moving average model's order is Q.The corresponding positions of the AR and MA parameters in the ARIMA model are detected using the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) curves.

B. FBProphet

Prophet is a method for forecasting time series data that matches non-linear patterns with seasonality on a yearly, monthly, and daily scale as well as the effects of holidays. It works well with historical information from different seasons and time series with sizable seasonal effects. Prophet typically does a good job of handling outliers and is tolerant of missing data and trend shifts. Prophet is a popular Facebook app that generates precise estimates for planning and goal-setting. We've discovered that it performs better than any alternative method in the vast majority of situations. We use Stan to fit models so that you may get forecasts in a matter of seconds.

An open-source time-series model creation method called Facebook Prophet combines some tried-and-true ideas with some fresh twists. It avoids some of the drawbacks of other techniques and excels at modelling time series with a variety of seasonalities. The total of the three-time functions plus an error term is growth g(t), seasonality s(t), holidays h(t), and error e(t).

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t$$

The growth function models the data's overall trend (and change points). Anyone with a basic understanding of logistic and linear functions should be familiar with the old concept. The increasing trend might exist in the data at any time or, as Prophet calls them, can change at "changepoints," according to the new idea added to Facebook Prophet. Data transitions from one direction to the next at changepoints. It may be explained, for instance, by the fact that new COVID-19 cases have started to fall after peaking following the introduction of vaccination. Another possibility is a sudden rise in cases brought on by the spread of a new strain throughout the population, and so on.

The growth function replicates the overall trend of the data, together with change points. The old idea should be familiar to everyone who has a basic understanding of logistic and linear functions. The increasing trend may exist in the data at any moment or may alter at "changepoints," as Prophet refers to them, is the novel idea added to Facebook Prophet. Changepoints are the instances at where the data shifts its direction. As an illustration, it could be explained by the fact that after peaking with the introduction of immunisation, new COVID-19 cases have started to fall. It might also be a sudden rise in instances brought on by the spread of a new strain throughout the neighbourhood, etc.

The holiday/event function: Facebook Prophet can be adjusted to anticipate when a significant event, like a holiday, will take place. It accepts a list of dates (US holiday dates are built-in, or you may enter your own dates), and when each date is included in the forecast, it adds or subtracts value from the projection based on previous data on the designated holiday dates.

$$s(t) = \sum_{n=1}^{N} (a_n\, cos(\frac{2\pi nt}{P}) + b_n\, sin(\frac{2\pi nt}{P}))$$

III. MODELING AND ANALYSIS

First we refine the data we have and then filter the data by removing all the null values and the invalid data. This processis called Data preprocessing.

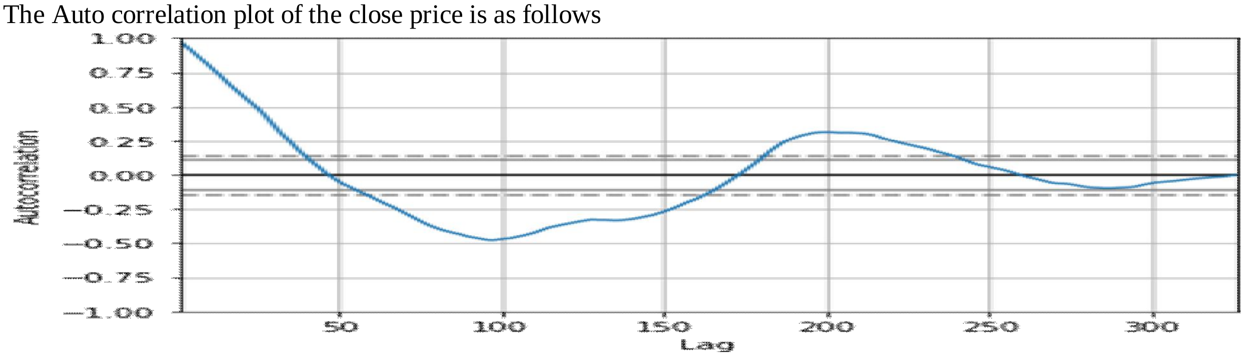
In order to predict the prices we had considered the Bitcoin price from April 2021.

Table-1

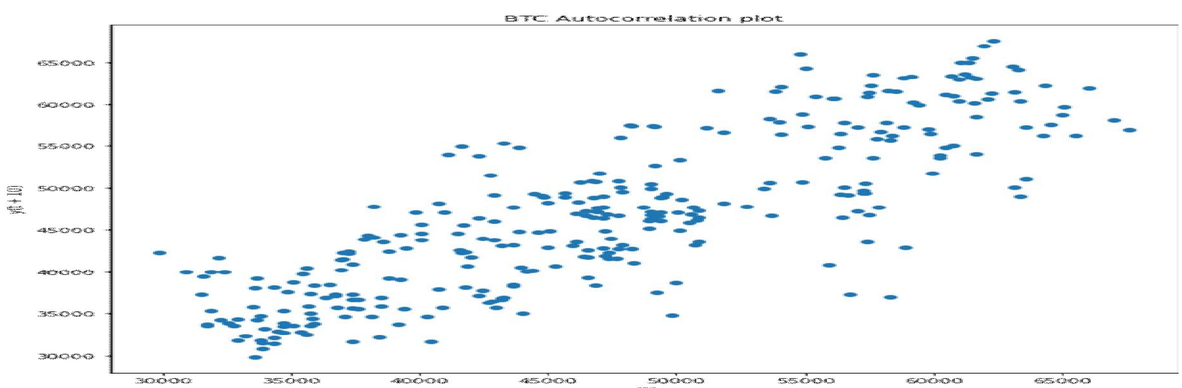
The table shows the tail end data of the dataset:-

Date	Open	High	Low	Close	Adj Close	Volume
2022-02-16	44578.277344	44578.277344	43456.691406	43961.859375	43961.859375	19792547657
2022-02-17	43937.070312	44132.972656	40249.371094	40538.011719	40538.011719	26246662813
2022-02-18	40552.132812	40929.152344	39637.617188	40030.976562	40030.976562	23310007704
2022-02-19	40026.023438	40418.878906	39713.058594	40122.156250	40122.156250	13736557863
2022-02-20	40119.890625	40119.890625	38185.878906	38251.500000	38251.500000	18199001088

The Auto correlation plot of the close price is as follows



The lag plot of Bit coin Auto correlation plot of the data is as follows:



The Bit coin lag plot The data's auto correlation graphic looks like this:

Modeling alongside Arima

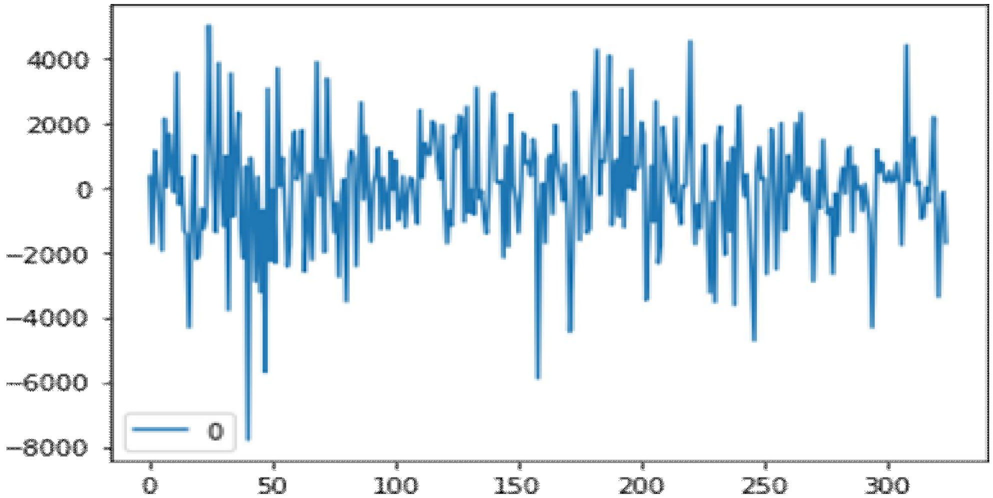
The ARIMA model that we suggested was trained using bitcoin closing prices. The arima model we suggested is created using the order (10, 1, 0). As a result, our suggested model has 10 autoregressive components, 1 nonseasonal difference required for stationarity, and 0 lagged forecast errors in the prediction equation.

The model summary of the ARIMA model is

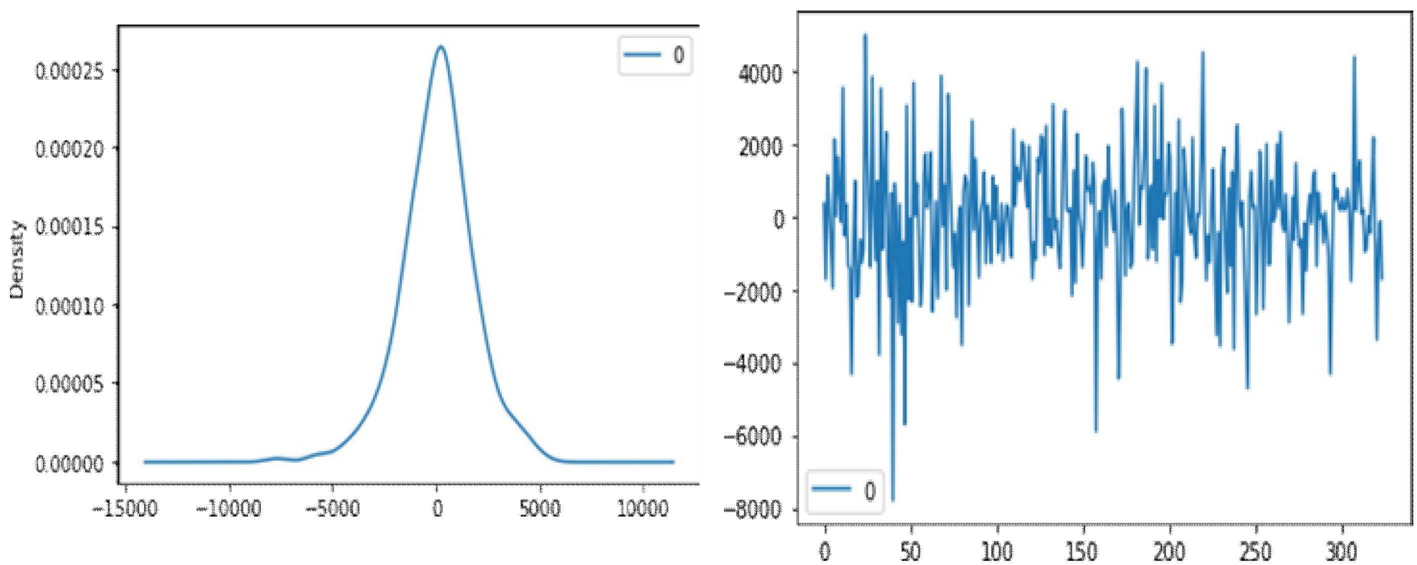
```
                             ARIMA Model Results
==============================================================================
Dep. Variable:                    D.y   No. Observations:                  325
Model:                ARIMA(10, 1, 0)   Log Likelihood               -2888.592
Method:                       css-mle   S.D. of innovations           1752.448
Date:                Sun, 20 Feb 2022   AIC                           5801.183
Time:                        09:50:42   BIC                           5846.589
Sample:                             1   HQIC                          5819.305

==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const        -64.9035     99.525     -0.652      0.515    -259.970     130.163
ar.L1.D.y     -0.0420      0.055     -0.757      0.449      -0.151       0.067
ar.L2.D.y     -0.0175      0.055     -0.318      0.751      -0.126       0.091
ar.L3.D.y     -0.0091      0.055     -0.166      0.868      -0.117       0.099
ar.L4.D.y      0.0965      0.055      1.744      0.082      -0.012       0.205
ar.L5.D.y      0.0050      0.055      0.091      0.928      -0.104       0.114
ar.L6.D.y      0.0114      0.056      0.205      0.838      -0.098       0.120
ar.L7.D.y     -0.0432      0.055     -0.780      0.436      -0.152       0.065
ar.L8.D.y     -0.0595      0.055     -1.075      0.283      -0.168       0.049
ar.L9.D.y      0.0969      0.055      1.748      0.081      -0.012       0.206
ar.L10.D.y    -0.0144      0.056     -0.259      0.796      -0.123       0.095
                                    Roots
==============================================================================
                   Real          Imaginary           Modulus         Frequency
------------------------------------------------------------------------------
AR.1            -1.1783           -0.3810j            1.2384           -0.4502
AR.2            -1.1783           +0.3810j            1.2384            0.4502
AR.3            -0.6024           -1.0938j            1.2487           -0.3301
AR.4            -0.6024           +1.0938j            1.2487            0.3301
AR.5             0.2367           -1.2201j            1.2428           -0.2195
AR.6             0.2367           +1.2201j            1.2428            0.2195
AR.7             1.1926           -0.8460j            1.4622           -0.0982
AR.8             1.1926           +0.8460j            1.4622            0.0982
AR.9             1.4767           -0.0000j            1.4767           -0.0000
AR.10            5.9503           -0.0000j            5.9503           -0.0000
------------------------------------------------------------------------------
```

The automated regressive plot of the Bitcoin price is as follows



The residuals plot description is as follows



count	325.000000
mean	-0.413476
std	1755.395293
min	-7760.464153
25%	-1039.865759
50%	89.539003
75%	996.336751
max	4997.563381

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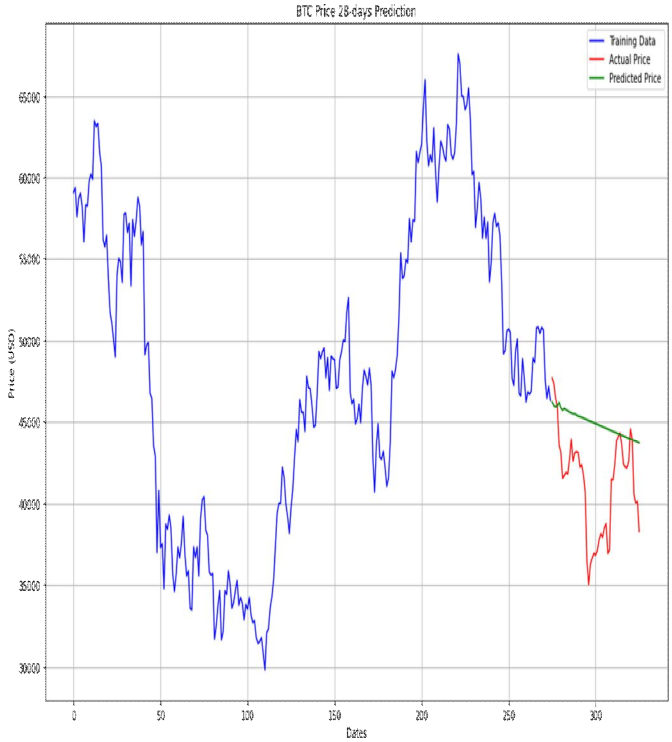
And our model has testing mean squared error of 185548.072.And here is the plot of the actual and mean predicted price.

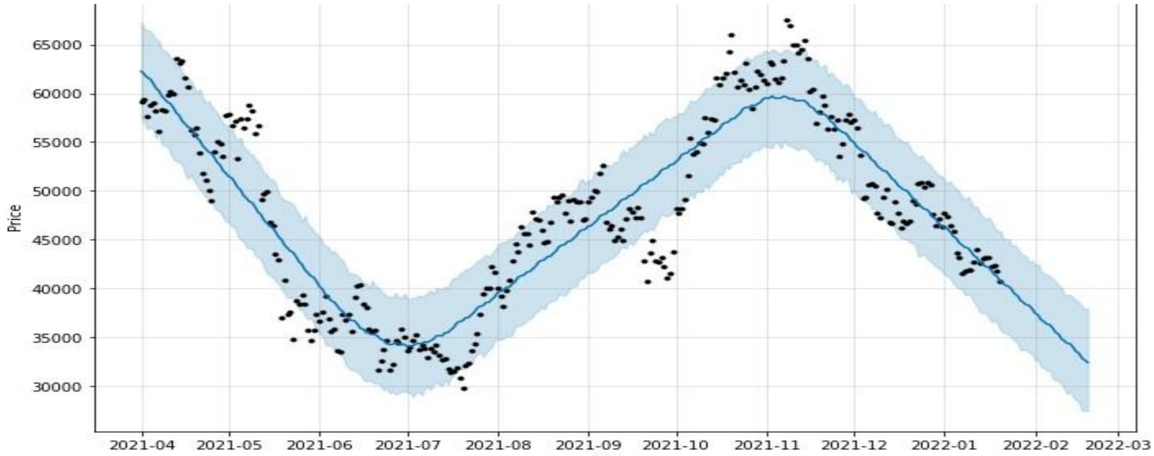


A. FBProphet Model

The FBProphet Model uses the same dataset as of the ARIMA model and we train the model with the same preprocessed data
The components modes of the FBProphet model is

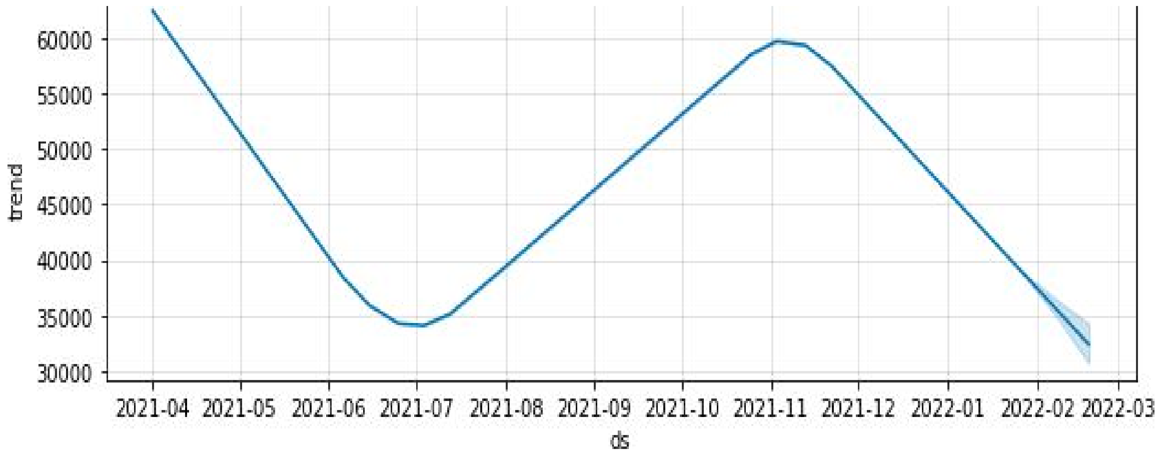
```
{'additive': ['weekly',
  'additive_terms',
  'extra_regressors_additive',
  'holidays'],
 'multiplicative': ['multiplicative_terms', 'extra_regressors_multiplicative'
]}
```

The model's plot looks like this:-

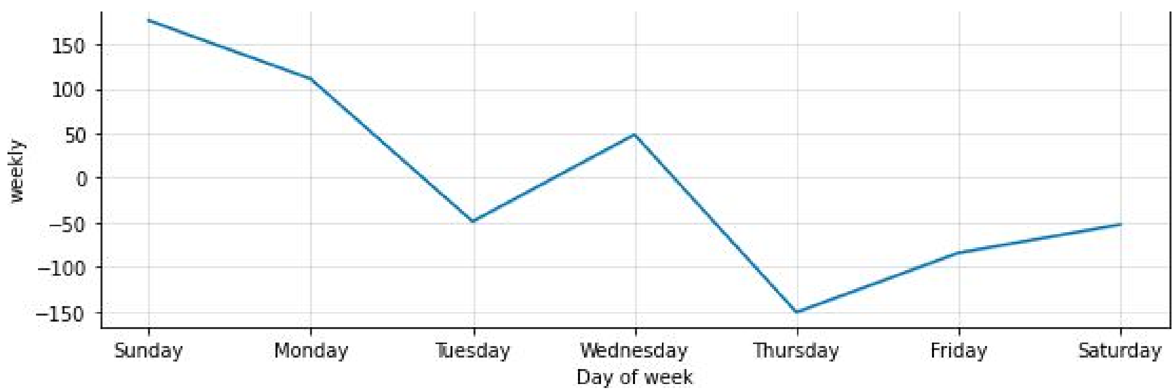


The component prediction of the model is

a)



b)



IV. RESULTS AND DISCUSSION

1) The Actual and the Predicted price comparison of the Arima model

2) The predicted price of the FBProphet model.The predicted outputs of the bitcoin for the next 30 days is shown in the given images

	ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper	additive_terms
295	2022-01-21	40595.845899	35412.144891	45199.053519	40595.845899	40595.845899	-84.036804
296	2022-01-22	40314.868992	35370.755583	45035.005117	40314.868992	40314.868992	-52.244005
297	2022-01-23	40033.892084	35226.124418	45045.208980	40025.326306	40035.429248	176.319639
298	2022-01-24	39752.915176	34912.356582	44332.078353	39725.325013	39782.412640	110.892792
299	2022-01-25	39471.938268	34614.011031	44464.132548	39427.995228	39527.704135	-48.840696
300	2022-01-26	39190.961361	34328.065862	44043.985087	39120.481950	39278.878246	48.452532
301	2022-01-27	38909.984453	33657.917845	43644.089396	38813.346783	39026.298334	-150.543457
302	2022-01-28	38629.007545	33733.749580	43403.977854	38498.195555	38795.552364	-84.036804
303	2022-01-29	38348.030637	33620.016889	43230.854046	38181.230863	38554.961191	-52.244005
304	2022-01-30	38067.053729	33410.018416	42692.310348	37847.279617	38317.605652	176.319639
305	2022-01-31	37786.076822	33229.439939	42821.220043	37527.873493	38103.145882	110.892792
306	2022-02-01	37505.099914	32579.915154	42365.532765	37200.336473	37907.397613	-48.840696
307	2022-02-02	37224.123006	32579.129548	42511.023008	36852.076520	37710.536018	48.452532
308	2022-02-03	36943.146098	31899.924296	41719.239492	36522.660940	37504.163164	-150.543457
309	2022-	36662.169191	31833.986100	41543.526917	36200.356919	37302.590005	-84.036804

additive_terms_lower	additive_terms_upper	weekly	weekly_lower	weekly_upper
-84.036804	-84.036804	-84.036804	-84.036804	-84.036804
-52.244005	-52.244005	-52.244005	-52.244005	-52.244005
176.319639	176.319639	176.319639	176.319639	176.319639
110.892792	110.892792	110.892792	110.892792	110.892792
-48.840696	-48.840696	-48.840696	-48.840696	-48.840696
48.452532	48.452532	48.452532	48.452532	48.452532
-150.543457	-150.543457	-150.543457	-150.543457	-150.543457
-84.036804	-84.036804	-84.036804	-84.036804	-84.036804
-52.244005	-52.244005	-52.244005	-52.244005	-52.244005
176.319639	176.319639	176.319639	176.319639	176.319639
110.892792	110.892792	110.892792	110.892792	110.892792
-48.840696	-48.840696	-48.840696	-48.840696	-48.840696
48.452532	48.452532	48.452532	48.452532	48.452532
-150.543457	-150.543457	-150.543457	-150.543457	-150.543457
-84.036804	-84.036804	-84.036804	-84.036804	-84.036804

	level_0	index	Date	Pred
320	320	320	2022-02-15	33522.582509
321	321	321	2022-02-16	33338.898830
322	322	322	2022-02-17	32858.925933
323	323	323	2022-02-18	32644.455677
324	324	324	2022-02-19	32395.271569

A simple price prediction of simple data is as given image:

multiplicative_terms	multiplicative_terms_lower	multiplicative_terms_upper	yhat
0.0	0.0	0.0	40511.809095
0.0	0.0	0.0	40262.624986
0.0	0.0	0.0	40210.211723
0.0	0.0	0.0	39863.807968
0.0	0.0	0.0	39423.097572
0.0	0.0	0.0	39239.413893
0.0	0.0	0.0	38759.440996
0.0	0.0	0.0	38544.970741
0.0	0.0	0.0	38295.786632
0.0	0.0	0.0	38243.373368
0.0	0.0	0.0	37896.969613
0.0	0.0	0.0	37456.259218
0.0	0.0	0.0	37272.575539
0.0	0.0	0.0	36792.602641
0.0	0.0	0.0	36578.132386

V. CONCLUSION

In this study, we looked at how well the ARIMA Model and FBProphet models predicted fluctuations in the price of bitcoin. Additionally, these models are used to forecast the price of bitcoin in the future.

By combining many features into a single feature and removing extraneous features, feature engineering can be used to increase the learning speed and accuracy of neural networks. Among the hyperparameters that can be changed are batch size, dropout rate, and weight initialization. We are also interested in investigating more complex deep learning models, including architectural variants of temporal convolutional neural networks and sequence to sequence models.

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