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Predicting Cryptocurrency Prices Comparing Different Machine Learning Techniques: A Performance Analysis for Pre and Post COVID-19 Pandemic Periods

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ABSTRACT

The main purpose of this paper is to compare the forecasting results of time series machine learning models to predict the cryptocurrencies' future prices for pre-COVID-19, during COVID-19 and post COVID 19 pandemics. Time series data collected from Yahoo Finance was used for the period between January 2017 till February 2024 as test data and the training data to predict 12 months from March 2024 till February 2025. The author undertook three machine learning models: SARIMA, LSTM and FbProphet for the forecasting analysis. LSTM model performs well in predicting the daily price forecasting as compared to SARIMA and Fb prophet models. Bitcoin is predicted to be in the range of $55000 to $65000 by February 2025. Results show a robust trend of volatility during COVID and post COVID periods and pre COVID period was not volatile resulting to no price movements. Based on the forecasting results post-COVID-19 pandemic, the LSTM model outperforms with better predictions than the other models. The findings also revealed that LSTM-RNN model can significantly increase the predictive power in the studies of deep learning models. This paper contributes to the literature on machine learning and forecasting models and the finding provides unique information while modeling the returns. It also insights on what machine learning model is the best to predict movements in the time series data. The results in this paper are expected to enhance our understanding on the role of machine learning models in forecasting future prices of investment instruments in the market, making it valuable for academics, investors, and policymakers alike.

Keywords: Cryptocurrencies, Bitcoin, Machine Learning, Deep Learning, Predictions, COVID-19
JEL Classifications: C45, C8, G2

1. INTRODUCTION

In the past, many viewed cryptocurrencies as a highly lucrative investment option within the financial market. However, the recent turbulence experienced in the crypto market has sent shockwaves through the entire ecosystem. Despite this disruption, technological advancements have propelled cryptocurrency transactions to notable levels of acceleration in recent years (Hughes et al., 2019). The realm of cryptocurrency has attracted attention from various sectors including the media, government officials, investors, scholars, and regulatory bodies, particularly following the notable surge and subsequent decline in 2017 often referred to as a "bubble" (Ftiti et al., 2023). According to the sociotechnical systems theory, the development of cryptocurrencies is divided into distinct components, including crypto operational services, governance structures, operating platforms, and practices. Nevertheless, there remains ongoing debate regarding whether cryptocurrencies meet the criteria to be classified as a legitimate asset class within the financial market (Panigrahi, 2023). Previously, cryptocurrency stood out as among the most lucrative investments for traders within the financial market. In just a span since November 2021, the collective market worth of cryptocurrencies experienced a

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remarkable surge, skyrocketing from under 20 billion US dollars in January 2017 to surpassing 3 trillion US dollars (Iyer, 2022). D'Ecclesia and Clementi (2021) mentioned that forecasting and adequately measuring volatility is very crucial for any portfolio selection and trading strategies. Investors react to the changes in volatility and thus, short- and long-term forecasting of future prices has been the key focus of countless research papers. Real-time forecasting of cryptocurrency prices just like that of other asset classes is of paramount importance for investors. As a result, it is not surprise that a growing body of research is looking at how well cryptocurrencies may be predicted using a variety of models (for example, Akyildirim et al., 2021; Awotunde et al., 2021; Derbentsev et al., 2020; Hitam and Ismail, 2018; Khedr et al., 2021, among others). Furthermore, major events like the COVID-19 pandemic and excessive liquidity have contributed to the emergence of abnormal returns in various risky investment assets (Kinateder and Choudhury, 2022). Notably, empirical evidence suggests that major cryptocurrencies as a measure of value during an extremely stressful time like COVID-19 for the financial markets (see, for example, Mnif et al., 2020; Ibrahim et al., 2022; González et al., 2021; Salisu and Ogbonna, 2022; Mariana et al., 2021, besides others).

The recent bankruptcy filing of FTX, a major cryptocurrency exchange valued at nearly $32 billion, has sent shockwaves through the crypto community and is disheartening news for investors. Concerns abound among investors who fear they may not recover their funds (Akyildirim et al., 2023). The collapse of FTX has triggered yet another wave of volatility in the intensely speculative market for digital assets. However, the foundation of the entire ecosystem is now shaken due to the recent turmoil in the cryptocurrency market. The collapse of the prominent cryptocurrency exchange FTX in November 2022 has garnered considerable attention, not only because of the significant losses suffered by investors, but also due to alleged breaches of corporate governance and public trust, although final legal determinations are pending. Moreover, the exchange's heavy reliance on the cryptocurrency bull market has exacerbated concerns. With the increasing interest in cryptocurrencies among investors, there are valid worries about the potential contagion effect on traditional markets (Yousaf et al., 2023). Consequently, forecasting cryptocurrency trends presents a formidable challenge for researchers, given the presence of unpredictable variables and the overall uncertainty prevailing within the crypto landscape.

In academic circles, there exists significant discourse surrounding whether cryptocurrency should be classified as a currency or an asset, with scholars such as Aslam et al. (2023), Cai et al. (2024), and others contributing to this debate. This discussion has been fueled by substantial price increases in cryptocurrency since 2017, coupled with pronounced levels of volatility. Figure 1 shows that prior to February 2017, the value of Bitcoin remained below $1000. However, by December 2017, it surged to a peak of $20,000 before plummeting to around $8000 in February 2018. Subsequently, in May 2018, it experienced another increase, surpassing $13,000, only to sharply decline to approximately $3000 by December 2018. The average price of Bitcoin in 2019 hovered around $7000. Notably, another indication of speculative activity emerged in Bitcoin post-2020 during the coronavirus (COVID-19) pandemic, with its value soaring to approximately $65,000 in December 2020, marking its highest point since its inception.

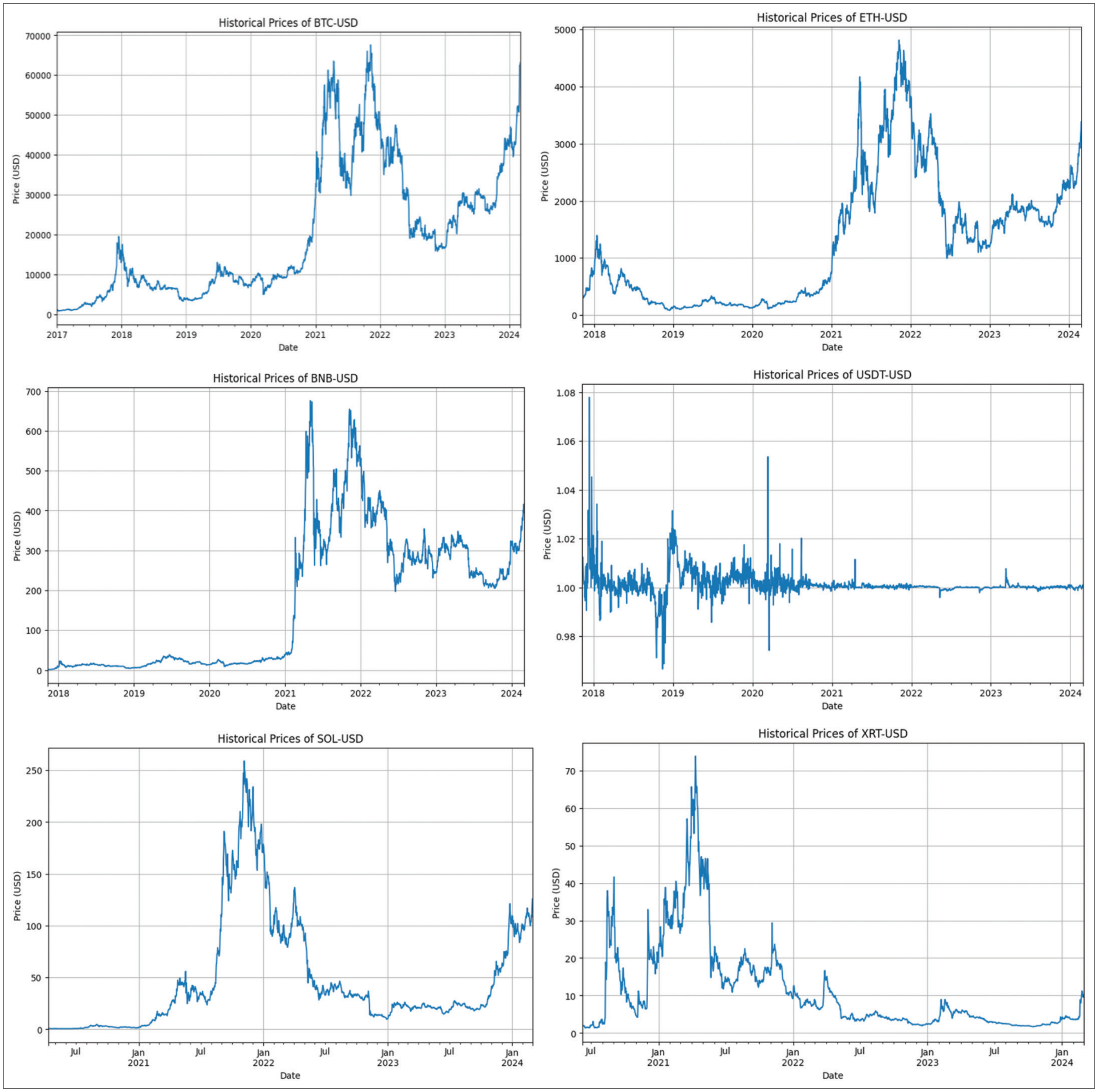
Since 2017, retail investors, regulators, policymakers, and the media have become more interested in the cryptocurrency market (Corbet et al., 2019). Since then there have been contradictory positions and the market remained a source of debate among research scholars. After 2017, due to massive surge in cryptocurrency price, there has been debate on whether they should be considered a currency or an asset or stable coins (Allen et al., 2022).

The swift expansion of the cryptocurrency market, characterized by its notable volatility and diverse applications in commercial transactions, has garnered significant interest from both scholars and investors (Tapia and Kristjanpoller, 2022). Similar to other financial time series, cryptocurrencies display heteroscedasticity, making the prediction of their volatility a complex endeavor crucial for effective risk management. In November 2021, Bitcoin (BTC) reached a milestone, soaring to $65,000, setting a fresh all-time high. This surge was attributed to the introduction of a Bitcoin ETF in the United States. Other notable price surges in 2021 were driven by developments involving Tesla and Coinbase. However, the unpredictability persists, partly fueled by speculation that a select few cryptocurrency holders possess a significant portion of the available supply. Consequently, the lack of reliable metrics makes it challenging to forecast cryptocurrency trends. Although cryptocurrency hasn't achieved widespread success as a stable unit of account or a hedge against inflation, it's beginning to gather momentum through an alternative narrative (Choi and Shin, 2023). Bitcoin, in particular, exhibits highly volatile exchange rates, presenting additional challenges for analytical research compared to traditional time series analyses unaffected by bank and government influence.

The body of empirical research concerning the modeling and prediction of cryptocurrency volatility is extensive, with a notable portion of literature employing traditional time series models, notably the generalized autoregressive conditional heteroscedasticity (GARCH) family of models (Amirshahi and Lahmiri, 2023). To foster innovation and protecting the society, the growing availability of data have allowed the machine learning models to be more predictive (Giudici and Raffinetti, 2021). Researchers have utilized various forecasting techniques, selecting them based on factors such as nature, quality, and accessibility of the data at hand. Time series models, for instance, aid in forecasting future values by analyzing past observations and regressing them against one another, with the effectiveness of these models often contingent upon the length of the forecasting horizon.

In recent times, the rise of Artificial Intelligence (AI) across various domains has spurred a growing interest in its application within financial markets, notably in stocks and cryptocurrency markets. Numerous studies indicate that Artificial Neural Network (ANN) models exhibit superior performance in volatility predictions compared to traditional GARCH-type models. This superiority

Figure 1: Depicts the daily cryptocurrencies prices from 2017 till February 2024



stems from their ability to capture the non-linearities inherent in the data series and their flexibility to model non-stationary series, as highlighted by Tapia and Kristjanpoller (2022). deep learning techniques have been increasingly employed for time-series forecasting, particularly in the dynamic realm of cryptocurrency markets. Many of these models feature distinctive architectural designs, incorporating neural and LSTM layers, alongside leveraging advanced deep learning methodologies to enhance accuracy and predictive capabilities (Akyildirim et al., 2021; Catania and Grassi, 2022; Ftiti et al., 2021). Chu et al. (2015) examined the returns between BTC-USD and discovered that the generalized hyperbolic distribution appears to be the best option for modelling. Furthermore, studies like (Alessandretti et al., 2018; Cerqueti et al., 2021; Zhang et al., 2022) used Support Vector Regression (SVR) and Artificial Neural Networks (ANN) models for forecasting and model accuracy. However, without utilizing any other exogenous variables, the time series model, sometimes referred to as the top-down model, creates an autoregressive relationship between the current and its lagged value. The ARIMA model proposed by Box and Jenkins is the most widely adopted time series model to forecast future prices. Numerous studies have used ARIMA-based models for short and long-range forecasting horizons (for example, Hernandez-Matamoros et al., 2020; Fan et al., 2021; Sharma and Bhardwaj, 2022, others). LSTM is another class of neural network model that gained popularity in forecasting due to its ability to forecast time series data accurately. LSTM uses internal memory based on sequences and makes future predictions (Bedi and Toshniwal, 2019). Similarly, Kim and Cho (2019) combining the convolutional neural network (CNN) with LSTM predicted the energy consumption on an hourly basis and delivered greater predictions as compared to other models like Multiple Linear Regression (MLR), Random Forest, SVR and multi-layer perceptions (MLP) models. Another dynamic time series model recently developed is Fb Prophet model which claims to solve the issue of ARIMA and LSTM models on the prediction accuracy level and fast computation. Firstly introduced by Taylor and Letham (2018) mentioned that Facebook Prophet fits non-linear trends with yearly, monthly, and daily seasonal as well as holiday influences. Recently, in the research performed by (Almazrouee et al., 2020), Fb prophet predicted better as compared to the Holt-Winters Model and displayed better generalizability. Few researchers like (Guo et al., 2020; Kim and Cho, 2019) have combined Fb prophet with LSTM for short-term predictions developing time series models. More in-depth comparative investigation on the strengths and weaknesses of forecasting models can be found in the referring works of Suganthi and Samuel (2012), Tealab (2018), Sezer et al. (2020) and Alsharef et al. (2022).

Apart from machine learning modeling, keyword analysis has also been performed by many studies to forecast. For instance, to find highly destabilizing patterns in new technologies, Dotsika and Watkins (2017) employed the keyword clustering method and reported considerable influence. Similarly to this, Dubey et al. (2019)'s research demonstrated how big data and predictive analytics could affect environmental and social sustainability. While numerous papers exist on volatility forecasting, only a handful focus on predicting the volatility of cryptocurrencies. Moreover, the majority of studies concerning cryptocurrency markets have primarily analyzed Bitcoin's data due to its significant market capitalization. To our knowledge, this study marks the first to leverage an extensive dataset encompassing multiple cryptocurrencies, demonstrating the efficacy of advanced machine learning models in volatility forecasting.

The study contributions are summarized as follows:

(a) The study investigated which machine learning model is the best in forecasting cryptocurrencies volatility.
(b) The study investigates and compares the performance of ML models, namely SARIMA, FBprophet, and LSTM, in forecasting the prices of cryptocurrencies.
(c) The study compared the ML models and its forecasting in different time periods (pre-covid, during covid and post covid pandemic).
(d) The study utilized a sizable dataset comprising six cryptocurrencies and 2700 observations to ensure the ability to draw generalizable and robust conclusions.
(e) The study applied formal statistical tests to assess differences in the performances of the models.

The subsequent sections of this paper are structured as follows: Section 2 elaborates on the methodological procedures employed in this study, detailing various machine learning models including FPProphet and LSTM networks. Section 3 outlines the experimental setup, methodology, and presents the results obtained, followed by discussions on those results. Lastly, Section 6 concludes the findings of this study.

2. METHODOLOGICAL PROCEDURES

Six major cryptocurrencies, namely, Bitcoin (BTC), Ethereum (ETH), Tether (USDT), BNB, USDC-USD and XRP- USD in terms of market capitalization were investigated.

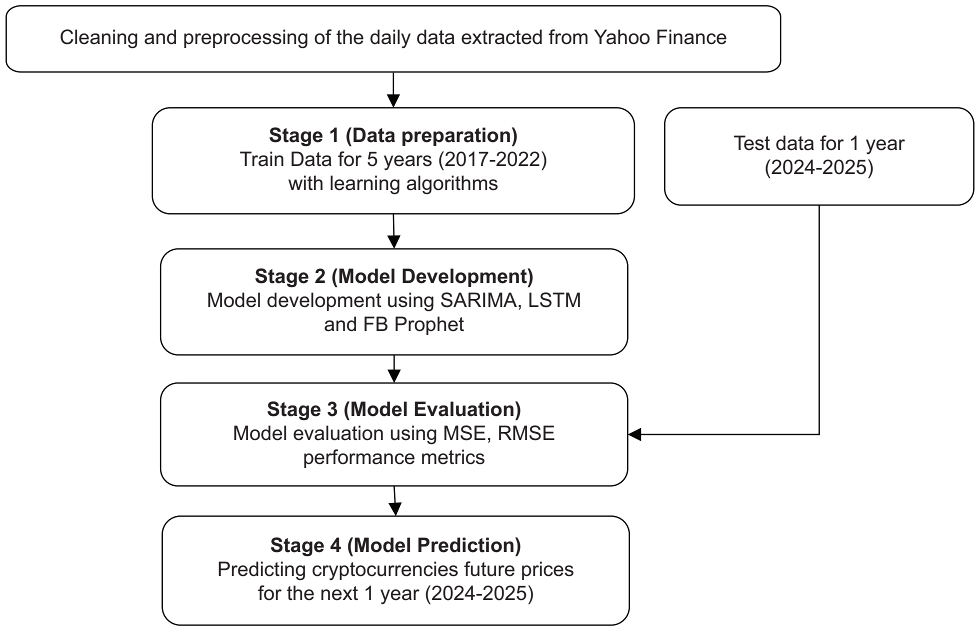
Figure 2 provides the research process and framework for predicting the future prices of six major cryptocurrencies. To achieve the study objectives, historical prices of six major cryptocurrencies were used for three different periods (1st January 2017 till 31st December 2019 – pre covid, 1st January 2020 till 31st December 2021 – during covid and 1st January 2022 till 29th February 2024 – after covid). All the historical data collected were at 1-day intervals. Daily data collected were preprocessed first in order to check data missing or inconsistencies.

Before proceeding with data preparation, data cleaning, and preprocessing, measures were taken to detect missing or NaN values to enhance prediction accuracy. In Stage 1, the data was trained over a span of seven years (2017-2024) using learning algorithms, with testing conducted over a 1-year period from 2024 to 2025. Subsequently, in Stage 2, models were developed employing SARIMA, LSTM, and Fb Prophet. Stage 3 involved evaluating the model's performance using metrics such as MSE and RMSE. Finally, in the last stage, the model was used to predict and compare a 12-month time series period. Three machine learning models for time series forecasting (SARIMA, LSTM, and Fb Prophet) were utilized to predict the prices of six major cryptocurrencies, followed by a comparison of their prediction outputs. Addressing non-stationary data is crucial as it can lead to unreliable and misleading results, hampering the accuracy of forecasts. Hence, a preprocessing step involved transforming the non-stationary data into stationary form through differencing the observations, thereby stabilizing the variance within the time series data.

2.1. Seasonal Auto Regressive Integrated Moving Average (SARIMA) Model

SARIMA, an extension of the ARIMA model, addresses a key limitation of ARIMA, which is its inability to handle time series data exhibiting seasonal patterns. The ARIMA model decomposes a given time series into components representing autoregressive (AR), integrated (I), and moving average (MA) variables (Dabakoglu, 2019). In the initial stage of constructing an ARIMA model, it's crucial to ensure that the mean, variance, and autocorrelation (reflecting linear relationships between lagged values) remain constant over time. The level of differencing needed to render a time series stationary is denoted by the order of the integrated term, represented as "d." The minimum number of preceding observations necessary to predict the current value is indicated by the order of the autoregressive (AR) term, denoted as "p." Similarly, "q" signifies the order of the moving average

Figure 2: Research method for the study



(MA) term, indicating the minimum number of lagged forecast errors required to predict the current value.

The mathematical equation for the SARIMA model, value at time t of a time series, y_t is represented in equation (1):

$$y_t = \beta_1 + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots \emptyset_p y_{t-p} + \omega_1 \varepsilon_{t-1} - \omega_2 \varepsilon_{t-2} - \ldots \omega_q \varepsilon_{t-q} \quad (1)$$

Where β is the constant term, ω and ∅ are the regression weights for the lagged observations and error terms, respectively. Seasonal variation is a significant contributor to non-stationarity in the majority of daily time-series datasets. For such circumstances, the SARIMA model is advised since it can manage trends and seasonal variations that are included in the time series.

2.2. Long Short-Term Memory (LSTM) Model

Deep learning employs a specialized architecture within artificial recurrent neural networks (RNN) called long short-term memory (LSTM). Unlike conventional feedforward neural networks, LSTM incorporates feedback connections, enabling it to effectively process sequential data. This architecture is capable of handling both entire data sequences and individual data points, making it versatile in applications ranging from timeseries forecasting to image processing. LSTM uses the backpropagation technique to find derivatives in the network by shifting layer by layer from the last to the first. Figure 3 shows the combined diagram of the RNN-LSTM model that was initially proposed by Donahue et al. (2015). The LSTM architecture comprises three main layers: (1) An input gate layer, responsible for controlling the flow of information into the network; (2) An input modulation layer, also known as the LSTM layer, which processes input sequences and manages information retention over time; and (3) An output layer, which receives the hidden state generated by the LSTM layer and produces the final predicted output value. In this process, the input layer feeds into the LSTM layer to generate the hidden state, which then passes through the output layer to generate the predicted value.

Traditional recurrent neural networks (RNNs) can capture intricate temporal patterns by mapping input sequences to hidden states, which are then used to generate outputs. However, LSTM (Long Short-Term Memory) networks introduce memory cells that incorporate three gates: an input gate, a forget gate, and an output gate, represented by the sigmoid function (σ). These gates control the flow of information within the memory cell, allowing it to selectively retain or discard information over time. The memory cell unit is calculated as the sum of the previous memory cell unit and the current state function, combined with the previous hidden state. In recent years, LSTM has gained widespread recognition for its effectiveness in various language-related tasks, such as speech recognition and machine translation.

2.3. Facebook (fb) Prophet Model

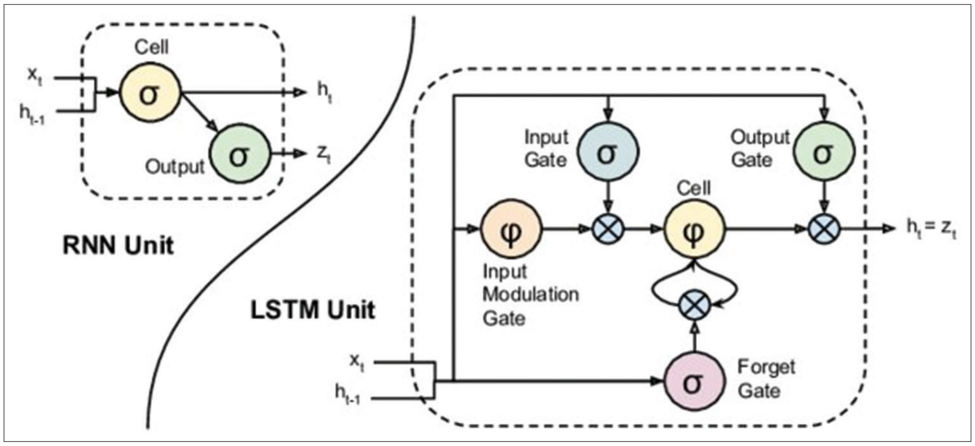
The most popular models for forecasting predictions are autoregressive models (Claeskens et al., 2007), which state that the output variable relies linearly on its prior values and a stochastic term. Facebook built the Prophet model to create a model that can detect seasonality in time series data and can do so using additive regression models to detect seasonality on a daily, weekly, and yearly basis (Taylor and Letham, 2018).

The mathematical equation for Fb Prophet model, value at time t of a time series, y_t is represented in equation (2):

$$y_t = g(t) + s(t) + h(t) + e(t) \quad (2)$$

Where, y_t is the output value $g(t)$ is the trend that Fb Prophet uses for trend forecasting, $s(t)$ represents periodic changes, $h(t)$ represents the effects of holidays and $e(t)$ is the error term, respectively. Despite dealing with large datasets comprising thousands of observations, the Fb Prophet model fitting process remains relatively fast and does not necessitate extensive data preprocessing. Moreover, it includes built-in mechanisms to handle missing data and outliers efficiently. Fb Prophet has been widely

Figure 3: Diagrammatic structure of LSTM-RNN model



Source: Donahue et al., 2015

used by many researchers like, (Jha and Pande, 2021; Battineni et al., 2020; Zhu et al., 2021) and many others due to the advantage of creating more accurate and reasonable forecasting that is much straight forward and smoothing parameters that are intuitive to non-experts.

The SARIMA, LSTM, and Fb Prophet models' predictive abilities are assessed at the model evaluation step by contrasting their test set predictions with the actual test set data. Two statistical metrics, MSE and RMSE, are used to compare the three models' prediction accuracy. The model with the lowest RMSE and MSE values is chosen to forecast the target variable, which is the future prices of six of the most popular cryptocurrencies from February 2024 to February 2025.

3. RESULTS

3.1. Stationarity Diagnostics

We defined the parameters and examined the time series stationarity before building the linear model. Augmented Dickey-Fuller (ADF) test, a promising technique was applied that is primarily used to examine the stationarity of financial time series (Yasir et al., 2021), and we assessed the outcome by looking at the P-value, one of the ADF's outputs. The confidence level for the P-value was set at 1%. Initially the P-value significant level was not below the threshold value of 1%, so we differentiated the dataset once (i=1) to generate a stationary time series. The ADF results for all three different periods indicated that the P-value was not significant initially, however, after the first difference the time series data remained stationary confirming the validation of the data for the modelling process.

Table 1 provides the descriptive statistics including mean, standard deviation, minimum, maximum and 25^{th}, 50^{th} and 75^{th} percentiles of the major cryptocurrencies for pre-COVID, during COVID and post-COVID-19 pandemic.

3.2. Seasonal Decompositions of the Major Six Cryptocurrencies

Seasonal decomposition entails breaking down a time series into its constituent components, including level, trend, seasonality, and noise. This decomposition process provides a useful conceptual framework for understanding time series data comprehensively, aiding in the identification and analysis of various patterns and trends. It facilitates better comprehension of the complexities involved in time series analysis and forecasting, offering insights into the underlying dynamics of the data (He et al., 2021). On a related note, forecasters need to be cognizant of seasonal influences and bubble behavior (Kinateder and Papavassiliou, 2021). Figure 4 shows the general direction of the series over a long period, a daily repeating pattern over a regular time interval due to seasonal factors and residuals that consists of fluctuations after the removal of previous components in the time series.

Volatility in daily price of cryptocurrencies greatly increased during the epidemic and the Russia-Ukraine crisis, making precise forecasting challenging. To assess the forecasting of cryptocurrencies, an original artificial intelligence methodology was utilized in place of the conventional time series models.

3.3. SARIMA Estimation

The multiplicative ARIMA, denoted as ARIMA (p, d, q) x (P, D, Q) s, is employed to address the seasonal patterns present in the time series data. Here, P, D, and Q represent the seasonal autoregressive, differencing, and moving average orders respectively, with 's' representing the number of seasons. Table 2 displays the coefficients and their corresponding significance levels following the estimation of the SARIMA model. The SARIMA model with an order of (2,1,1) and seasonal order of (4,0,3,12) was selected due to its superior accuracy in forecasting daily price changes. Taneja et al. (2016) stated that seasonality in the statistical models is used to determine future trends and seasonal differentiation is performed to make the data stationary. The heteroscedasticity tests statistics value and the $P < 0.000$ indicated that we reject the null hypothesis that residuals have no variance. The coefficients of all parameters like ar, ma, ar.S and ma.S are statistically significant as indicated by the p values less than 0.05 and 0.001.

Comparing the SARIMA model results for pre, during and post-COVID-19, it was noticed that there was seasonal during the COVID-19 pandemic, as the AIC value was at the lowest level.

Table 1: Descriptive statistics of the major cryptocurrencies

Descriptive	BNB-USD	BTC-USD	ETH-USD	XRP-USD	USDC-USD
From 1-03-2020 till 31-12-2021 (during Covid-19)					
Mean	21.35	11116.38	307.54	1.00	1.00
Std	6.26	4305.86	144.18	0.01	0.00
Min	9.39	4970.79	110.61	0.97	0.97
25%	16.43	8876.62	200.71	1.00	1.00
50%	19.63	9713.49	244.96	1.00	1.00
75%	27.62	11679.55	388.93	1.00	1.00
Max	38.95	29001.72	751.62	1.04	1.05
From 1-10-2018 till 28-02-2020 (pre-COVID 19)					
Mean	17.85	7198.03	179.44	1.01	1.00
Std	8.59	2547.38	50.78	0.01	0.01
Min	4.53	3236.76	84.31	0.99	0.97
25%	9.81	4262.78	139.52	1.00	1.00
50%	17.42	7436.30	174.55	1.00	1.00
75%	22.88	9323.63	209.98	1.01	1.01
Max	38.82	13016.23	336.75	1.04	1.03
From 1-1-2022 till 29-2-2024 (post COVID-19)					
Mean	330.94	29446.45	2072.06	1.00	1.00
Std	72.89	10030.44	777.28	0.00	0.00
Min	197.04	15787.28	993.64	1.00	1.00
25%	275.97	20211.03	1338.02	1.00	1.00
50%	306.64	24402.82	1793.57	1.00	1.00
75%	392.44	39594.33	2821.68	1.00	1.00
Max	531.40	47686.81	3829.56	1.00	1.00

Figure 4: Seasonal decomposition of BTC-USD (a), Seasonal Decomposition of ETH-USD (b), Seasonal Decomposition of Tether (USDT)-USD (c), Seasonal Decomposition of BNB-USD (d), Seasonal Decomposition of USDC-USD (e), and Seasonal Decomposition of XRP-USD (f) for the period 2017-2022

Table 3 provides the performance metrics of the forecasting models for the six major cryptocurrencies during different periods. The models exhibited comparable performance metrics across pre-COVID, during COVID, and post-COVID-19 pandemic periods. Analysis of these metrics suggests that the models may have excessively fitted the training data, resulting in an inability to accurately forecast price movements. Surprisingly, the inclusion of all cryptocurrencies in the dataset appears to have contributed to the development of prediction models with enhanced classification performance.

Table 4 provides the price forecast for the major cryptocurrencies based on market capitalization. The comparative analysis indicates that LSTM is a better ML model giving better RMSE and MSE performance metrics as compared to SARIMAX and FbProphet ML models. Bitcoin price is forecasted to be \$64467, followed by Ethereum price to be \$2785, USD Coin to be \$1.0003, Binance coin to be \$354.05 and XRP to be \$0.478 by LSTM model. As per SARIMAX model, bitcoin price is forecasted as \$51770, Ethereum price forecasted as \$3341, tether coin was forecasted as \$1.0004, binance coin was forecasted

Table 2: SARIMA estimation for daily price of cryptocurrencies (Pre-COVID, during COVID and Post COVID-19 pandemic)

Covariance type	BTC-USD	ETH-USD	USDT-USD	BNB-USD	USDC-USD	XRP-USD
Coefficients of SARIMA estimation pre COVID 19 Pandemic						
ar.L1	0.0981	−0.8786***	0.4225	−0.7447		
ar.L2	−0.0776	0.0193**	0.1250			
ar.L3						
ma.L1	−0.7611	0.9217***	−0.9043	0.7948	−0.6442	−0.7569
ma.L2						
ma.L3						
ar.S.L12	0.0992	0.7810***	0.0897			
ar.S.L24	−0.0807	0.4144***				
ar.S.L36	−0.2068	−0.6047**				
ar.S.L48	0.1179**	−0.0975				
ma.S.L12	−0.1011	−0.8666***				
AIC	−4371	7297	−5889	1999	−3544	−748
H	0.1200***	0.0400***	0.2900***	0.8800	0.2700***	1.6900
Coefficients of SARIMA estimation during COVID 19 pandemic						
ar.L1	−0.9874***	−0.1098**	0.1254**		−0.1951***	
ar.L2			0.076***		−0.2278***	
ar.L3						
ma.L1	0.9768**		−0.9632***		−0.3698**	−0.9605***
ma.L2						
ma.L3						
ar.S.L12	0.6352***					0.0576***
ar.S.L24	0.1015***					
ar.S.L36	−0.1249***					
ar.S.L48						
ma.S.L12	−0.7324***	−0.0835	0.041			
AIC	12605	8861	−6238	6238		−6313
H	28.0800***	1.9700***	0.0100***	521.400***	1.7100***	0.0100***
Coefficients of SARIMA estimation post COVID 19 Pandemic						
ar.L1	0.7686	0.678	0.3371	0.2122	0.0428***	−0.8403***
ar.L2	0.0440	0.067	0.0763	0.1267***	0.5385***	
ar.L3						
ma.L1	−0.7904	−0.845	−0.8459	−0.3394**	−0.7611	0.8326***
ma.L2						−0.0099
ma.L3						−0.075***
ar.S.L12	−0.8601	0.490	0.1336	−0.2710***	−0.6375	0.044
ar.S.L24	0.6019	−1.064	0.0882	0.9142***	0.124	0.0750***
ar.S.L36	0.6400	−0.263	0.0622	0.3261***		−0.0650
ar.S.L48	−0.0362	0.172	0.0689	−0.088***		
ma.S.L12		0.8052	−0.1391	0.2266**	0.0759***	
AIC	42806	26247	−19294	2568	8044	5343
H	0.741***	0.622***	0.01***	0.46***	1.71***	0.02***

P<0.05**, P<0.001***. AIC: Akaike Information Criterion, H: Heteroscedasticity, ar: Autoregressive, ma: Moving average

to be at $403.99, USD coin was forecasted at $1.000 and XRP forecasted at $0.5757. Finaly, Fbprophet forecasted bitcoin price at $55656, Ethereum at $3006, tether coin at $0.998, binance coin at price $254 followed by USD coin forecasted at $1.002 and XRP at $0.7232.

3.4. Model Comparison

Test result predictions of daily price change for 12 months were obtained using SARIMA, LSTM and Fb Prophet models for three different periods between 2017 and 2024. Figure 5 provides the forecasting models post-COVID-19 pandemic for 12 months with actual prices, ARIMA, LSTM and Fb Prophet model predictions. A visual comparison of post-COVID-19 pandemic is shown in Figure 5. Performance metrics (MSE and RMSE) values are provided in Table 3. LSTM and SARIMA models had delivered smaller performance metrics value than Fb Prophet. Furthermore, the pre-COVID (Figure 6) and during the COVID-19 pandemic (Figure 7) comparison showed that LSTM model predictions were almost similar to the actual cryptocurrency prices. The performance metrics were also found to be supportive at the significant level of $P < 0.001$. LSTM model due to its best performance metrics outperformed SARIMA and Fb Prophet models while comparing the cryptocurrency price predictions in different time series dataset. This research was also supported by Cao et al. (2019), Livieris et al. (2020), Khodabakhsh et al. (2020), among others who found that LSTM display a better time series forecasting and provides greater accuracy in better decision making.

Forecasting models during and pre-COVID-19 pandemic is shown in Figures 6 and 7. Comparing the forecasting for pre, during and post-COVID pandemic, it was found that the forecasting models predicted accurately during COVID-19 as the performance metrics (MSE and RMSE) were having low

Table 3: Performance metrics of forecasting models for cryptocurrencies

Cryptocurrencies	Performance metrics	ARIMA	LSTM	Fb Prophet
(a) Comparing forecast models pre COVID-19 level (1-1-2017 till 31-12-2019)				
BTC-USD	MSE error	4464.25	0.002	42710216.700
	RMSE error	1.99	1.078	6535.5
ETH-USD	MSE error	4.15	0.005	203317
	RMSE error	2.03	1.940	450.800
USDT-USD	MSE error	2.29	0.005	0.000
	RMSE error	0.09	1.565	0.010
BNB-USD	MSE error	1189.68	0.003	53.820
	RMSE error	34.49	1.095	7.330
USDC-USD	MSE error	1.43	0.007	5.800
	RMSE error	0.003	1.935	0.007
XRP-USD	MSE error	6.76	0.004	0.000
	RMSE error	0.002	2.046	0.016
(b) Comparing Forecast models during COVID-19 level (1-1-2020 till 31-12-2021)				
Cryptocurrencies	**Performance metrics**	**ARIMA**	**LSTM**	**Fb Prophet**
BTC-USD	MSE error	5375892	0.009	1782182161
	RMSE error	2318	1.735	42215
ETH-USD	MSE error	23407	0.004	11371679.3
	RMSE error	152	1.757	3372
USDT-USD	MSE error	4.06	0.007	4.49
	RMSE error	0.000	2.071	0.000
BNB-USD	MSE error	264.9	0.003	182806
	RMSE error	16.4	1.726	427.6
USDC-USD	MSE error	5.54	0.008	7.00
	RMSE error	0.00	1.804	0.000
XRP-USD	MSE error	5.23	0.006	6.58
	RMSE error	0.000	1.28636	0.000
(c) Comparing forecast models post COVID-19 level (1-1-2022 till 29-2-2024)				
Cryptocurrencies	**Performance metrics**	**ARIMA**	**LSTM**	**Fb Prophet**
BTC-USD	MSE error	326735.7	0.008	13202408
	RMSE error	571.6	1.743	3633.5
ETH-USD	MSE error	114523.5	0.004	38450
	RMSE error	338.4	1.825	196.08
USDT-USD	MSE error	7.5	0.006	6.09
	RMSE error	0.0	2.014	0.02
BNB-USD	MSE error	342.4	0.005	7156.1
	RMSE error	18.5	1.099	84.59
USDC-USD	MSE error	53.1	0.008	2837.07
	RMSE error	7.2	2.134	53.17
XRP-USD	MSE error	4.8	0.001	43.84
	RMSE error	23.9	1.064	6.621

Table 4: Prediction price of cryptocurrencies by comparing SARIMAX, LSTM and FbProphet ML models

CRYPTOCURRENCIES	CLOSE @ 29th February 2024	SARIMAX	LSTM	FBPROPHET
BTC-USD	61198.38	51770.36	64467.428368	55656.670789
ETH-USD	3341	2785	2268	3006
USDT-USD	1.0004	1.0003	0.9999	0.9983
BNB-USD	403.99	354.05	784.988	254
USDC-USD	1.000	1.000	0.996	1.002
XRP-USD	0.575	0.555	0.478	0.723

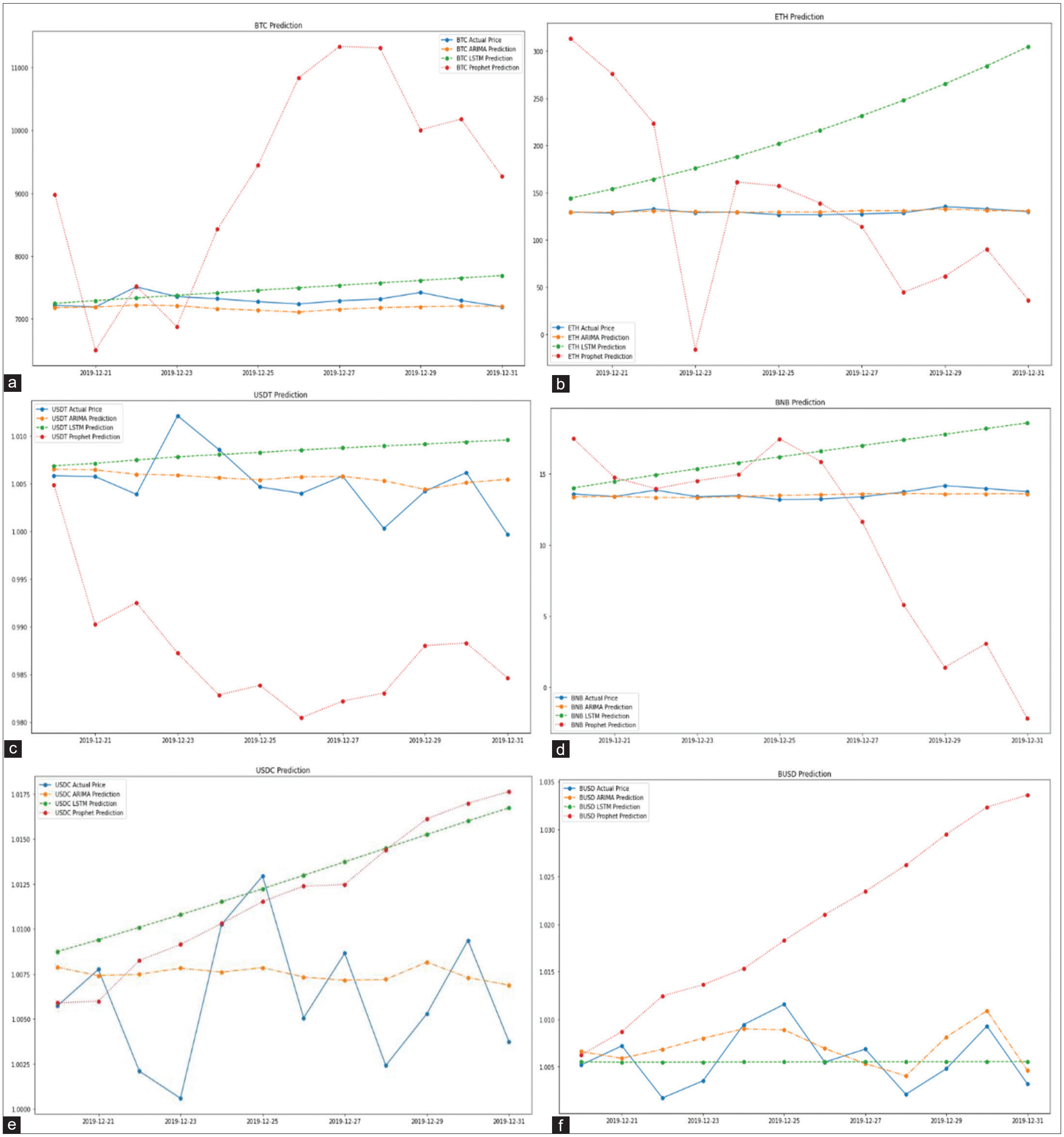
value and significance. Furthermore, the comparative figures also indicated that the actual price and predicted price by the models were in line with each other, especially the LSTM model. Based on the Fb prophet model forecasting, bitcoin price is likely to go below $55,000 within 12 months, followed by Ethereum prices are expected to near $3341 and remain above the actual price as of 29th February 2024, tether price is likely to go below $0.998 within 12 months, whereas BNB price is expected to reach $403 and above the actual price of $300 as of 29th February 2024. Finally, USD coin and Binance coin are expected to remain stable and above the actual current price within the upcoming 12 months. Fb Prophet predicted bitcoin, Ethereum and BNB to further increase in price than it was actually at that time (Figure 7). However, after comparing the current cryptocurrency prices, it is confirmed that Fb Prophet is unable to predict the seasonal trends more accurately as compared to SARIMA and LSTM. Jha and Pande (2021) while performing the sales prediction, found that Fb prophet showed improved performance in terms of accuracy in predicting due to its low error and better accuracy. In recent study, Agosto and

Figure 5: Assessing the three forecasting models post COVID-19 pandemic for 12 months from February 2024–February 2025. (a) BTC-USD, (b) ETH-USD, (c) USDT-USD, (d) BNB-USD, (e) XRP-USD, (f) USDC-USD

Cafferata (2020) tested the individual cryptocurrencies and its forecasting during bubbles, and found that Ethereum signaled rapid increase in price during bubble periods, however, Bitcoin was significant in explaining price dynamics, but was unable to predict strong evidence of price movement during bubble periods. Similarly, Battineni et al. (2020) while conducting COVID-19 analysis found that Fb Prophet is a perfect model for non-linear trends. In addition, Dash et al. (2021) mentioned that Fb Prophet works primarily on one time series, and its performance varies by different dataset.

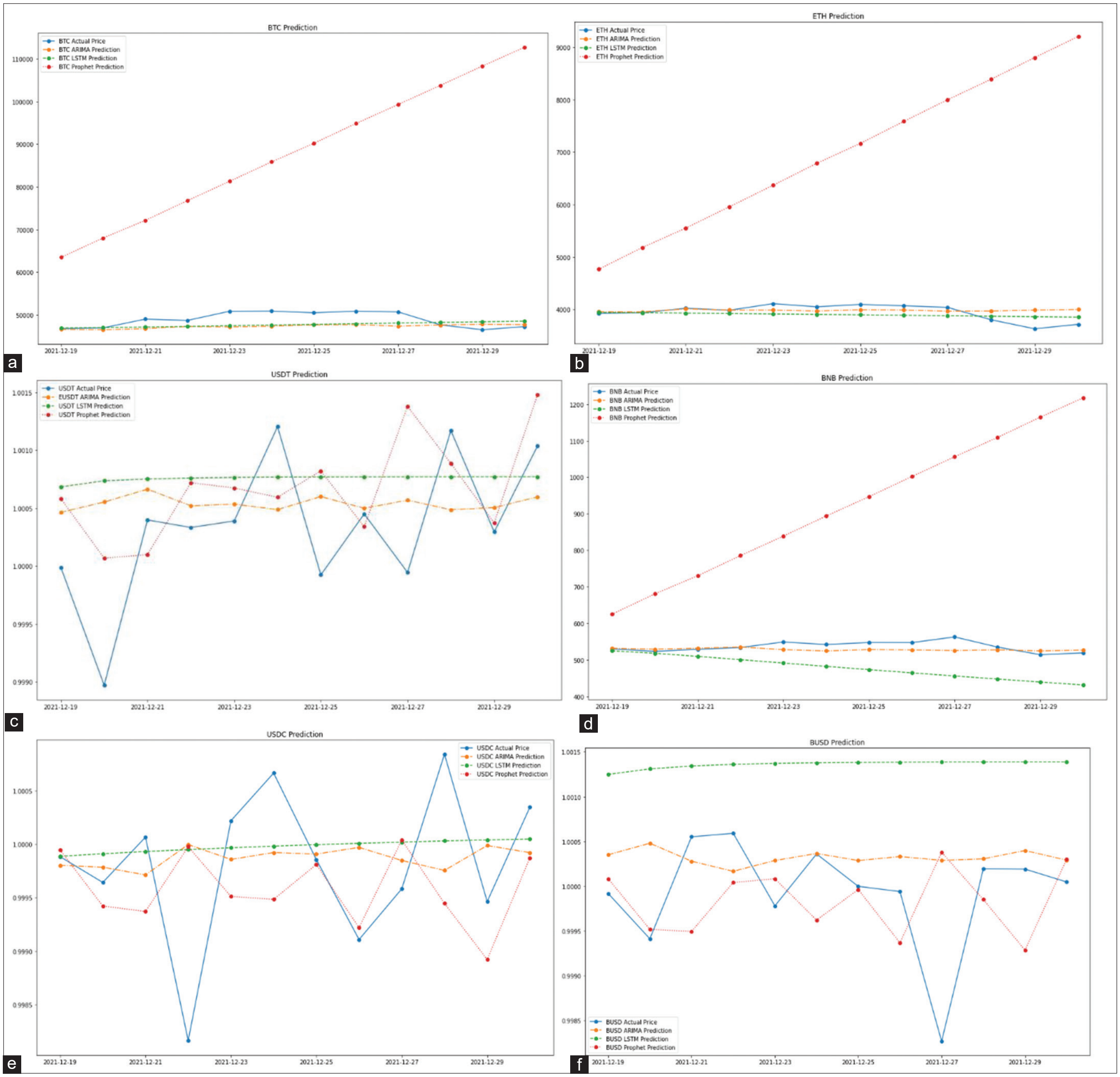
LSTM has predicted Ethereum price to be below $2500 which is far from the current market price of $3400. Fb prophet has given the prediction price of $3100, followed by $2800 by the SARIMA modelling. However, as the prediction is done for the coming 12 months, it is not justified to compare the actual price

Figure 6: Assessing the three forecasting models pre COVID-19 pandemic for 12 months from 2017 till February 2020. (a) BTC-USD, (b) ETH-USD, (c) USDT-USD, (d) BNB-USD, (e) XRP-USD, (f) USDC-USD



with the predicted ones. The surge in Bitcoin can be linked to the implementation of An Exchange-Traded Fund (ETF) linked to Bitcoin that provides investors with the opportunity to invest in Bitcoin indirectly, without needing to possess the actual cryptocurrency. Upon its introduction, a Bitcoin ETF often draws substantial investments from conventional investors who hadn't ventured into cryptocurrencies before. This surge in investment can drive up demand for Bitcoin, consequently pushing its price higher. Furthermore, the inception of Bitcoin ETF can enhance Bitcoin's credibility as a viable investment, fostering greater trust among investors and contributing to price appreciation. This research finding while performing seasonal trends confirms that Fb Prophet showed inferior performance metrics, and the forecasting is far from the actual cryptocurrency prices. This may be due to the different time series and dataset comparison performed in this study. However, it is a matter of further investigation.

Figure 7: Assessing the three forecasting models during the COVID-19 pandemic for 12 months from March 2020 till December 2021. (a) BTC-USD, (b) ETH-USD, (c) USDT-USD, (d) BNB-USD, (e) XRP-USD, (f) USDC-USD



4. CONCLUSION AND POLICY IMPLICATIONS

This study undertook a comprehensive comparison of three distinct ML models for price forecasting within the cryptocurrency market data context as first contribution: (1) SARIMA-type models as traditional time-series models, (2) LSTM models representing popular deep learning approaches, and (3) FbProphet models as additive models. Our experimental findings, based on data from six major cryptocurrencies, revealed that our deep learning models consistently outperformed SARIMA and Fbprophet models, irrespective of any distribution assumption made for the residuals.

The cryptocurrency market's modeled facts demonstrate that it was characterized by quick price fluctuations and considerable uncertainty, which raises the issue of prediction during the COVID-19 pandemic situation. All three models were trained using 5 years of daily time series data from January 2017 to February 2024. When predicting 12 months of unseen data, the LSTM model demonstrated strong performance in forecasting the daily prices of Bitcoin, Tether, USDC, XRP-USD, and Binance Coin, achieving low mean squared error (MSE). However, it exhibited poorer performance in predicting the prices of Bitcoin and Ethereum, resulting in higher error metrics. On the other hand, SARIMA and Fb Prophet models yielded higher prediction errors compared to LSTM. SARIMA forecasts for the period from

2024 to the end of 2025 suggested that the prices of Bitcoin and Tether are likely to decline further, while Binance Coin, USDC, Ethereum, and XRP are expected to remain relatively stable during this period. Similarly, SARIMA predicted no huge movement in the price of bitcoin, Ethereum, Tether and Binance, BNB was predicted to lower further, and USD Coin will see a slight increase in price. Based on the forecasting results post-COVID-19 pandemic, the LSTM model outperforms with better predictions than the other models. It was believed that LSTM model due to its neural networking ability would have best predictive capacity, however, due to its lack of data processing, it has not been utilized extensively as machine learning approaches (Ma, 2020).

Second contribution involved evaluating the predictive performance of cryptocurrency prices across various time periods (pre-COVID, during COVID, and post-COVID) using ML models, and comparing the error metrics. Both contributions—employing a comprehensive set of cryptocurrencies and conducting hypothesis tests—enabled us to assess the validity of our assertions and demonstrate the superior performance of neural networks. Based on the results, it was found that prediction performed better during COVID and post covid indicating that volatility play an important role in determining the predictive prices of cryptocurrencies. SARIMA and Fb Prophet forecasting models were found inferior to LSTM as their forecasts were not reliable due to large prediction errors. Forecasts made with Facebook Prophet also did the greatest job of capturing the temporal patterns found in the observed data. Therefore, when forecasting demand, the LSTM model should be chosen over others.

Traditional methodologies have often overlooked the development of an intricate training dataset enriched with comprehensive data, opting instead to enhance forecasting accuracy through the utilization of advanced models and procedures. Specifically, they neglect to analyze each cryptocurrency independently, disregard potential inter-cryptocurrency connections, and overlook the intricate and ever-changing nature of cryptocurrency time-series data. This study advocates an alternative approach, proposing a novel methodology aimed at crafting accurate and dependable forecasting models. However, this was also one of the limitations that this study compared three different forecasting models, despite having many different machine learning and traditional time series forecasting approaches. Furthermore, another interesting direction for future research could be to compare the proposed model with traditional forecasting modelling approaches.

Comparing the forecasting models of six major cryptocurrencies, Bitcoin and Tether are predicted towards more downside pain in the coming months. Future forecasts also indicate that USD Coin and Binance Coin will outperform the cryptocurrency market due to their stable coin advantages and pegged to the United States Dollars. The findings presented in this paper will be useful to practitioners and policymakers for medium- to long-term planning on cryptocurrency laws and exposed risks. The author acknowledges that greater regulatory direction is required to promote the industry's healthy growth and lessen speculation in cryptocurrency assets. Additionally, the cryptocurrencies used in this study were chosen because they represent the ones with the largest market capitalization. The proposed effort should therefore be viewed as a first step in improving forecasting performance regarding predicting future cryptocurrency prices. The addition of new cryptocurrencies could expand the proposed methodology. This is the main concern for future research because an extension with other cryptocurrencies could offer new factors that could theoretically influence and improve predicting performance, demanding more studies. In summary, this research reinforces the notion that price manipulation can significantly distort the cryptocurrency market. Prices in this realm are influenced by factors beyond typical supply, demand, and fundamental news. The repercussions of these distortions, once they unravel, may lead to substantial downward pressure on cryptocurrency prices. The study results affirm the long-standing belief that questionable activities relate to bubbles and can make price distortions worse.

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