CryptoProphet:
Building a Cryptocurrency Portfolio App with Integrated Market Predictive Model

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Agenda

Background
Problem Statement
Motivation
Related Work
Project Overview
Data Collection and Preprocessing
Technical Architecture
Data Analysis
Model Selection
Individualized Model Selection
Results
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Demo
Q&A

Background

- **Cryptocurrency is a type of digital currency that uses cryptography for security**
- **Cryptographic techniques ensure the integrity and security of transactions**
- **It operates on decentralized networks based on blockchain technology**
- **All transactions are recorded on a public ledger, the blockchain, which is accessible to anyone**
- **Rapidly transformed the financial landscape since introduction of Bitcoin (2009)**
- **It offers a decentralized, peer-to-peer system for transaction**

Problem Statement

- Cryptocurrencies are know for their high volatility, making it challenging for traders to make informed decisions
- Reports from the IMF and BIS highlight the substantial financial losses that occur due to the volatility and unpredictability of the crypto market
- These losses are often exacerbated during periods of market stress and can affect both individual and institutional investors.
- The volatility and unpredictability of the cryptocurrency market leads to significant financial losses.
- There is a need for a predictive model portfolio app that can quickly adapt to market changes and provide reliable forecasts.

Motivation

To provide a reliable app for crypto investors community

- predict their cryptocurrency prices
- simplify the process of their portfolio management
- enhance decsision-making through advanced predictive analytics and real-time data integration

Related Work

No	Author	Year	Technique	Crypto	Dataset Source	Data Range	Prediction Methods
1	Nair et al.	2023	DL	BTC	Kaggle	Sep 17, 2014 – Feb 01, 2022	LSTM, RNN, GRU, BiLSTM
2	Mohammed et al.	2022	DL	AMP, ETH, XRP, Electro-Optical System	CoinMarketCap	May 2015 – Apr 2022	LSTM
3	Helder et al.	2021	DL, ML	BTC, ETH, LTC	CoinMarketCap	Aug 07, 2015 – Mar 03, 2019	Linear Model, RF, SVM
4	Jin et al.	2023	DL	BTC, ETH	CoinMarketCap	Jul 23, 2017 – Jul 15, 2020	VMD, GRU, LSTM
5	Hamayel et al.	2021	DL, ML	BTC, ETH, LTC	csv	Jan 1, 2018 – Jun 30, 2021	LSTM, GRU, Bi-LSTM
6	Kan et al.	2022	DL	BTC, ETH, Ripple	Kaggle	Jan 1, 2012 – Mar 31, 2021	1DCNN, GRU
7	Erdinc et al.	2021	DL, ML	12 Crypto	Bitfinex, Kaiko	April 1, 2013 – June 23, 2018	LR, RF, SVM, ANN
8	Irfan	2022	ML	BTC	CoinDesk	Jul 18, 2010 – Aug 30, 2020	AMT, RF, MLR, MLP
9	Miller et al.	2021	DL, ML	10 Crypto	CoinMarketCap	Jan 1, 2027 – Jul 14, 2021	LSTM, RNN, DNN
10	Rather et al.	2023	DL, ML	BTC, DOGE, ETH, ADA	CoinMarketCap	Jan, 2020 – Apr, 2022	SVM, DNN, ARM
11	Cocco et al.	2021	DL, ML	BTC, ETH	CoinMarketCap	Jan 1, 2017 – Apr 30, 2020	LSTMNN, FFNN, BNN, SVM, ANN, RF
12	Phumudzo et al.	2023	DL	BTC, LTC, ETH	Yahoo.com	Jan 1, 2018 – Jan 1, 2023	LSTM, GRU, Bi-LSTM
13	Patel et al.	2020	DL	BTC, ETH, LTC	Bitinfocharts.com	Ju, 2017 – Dec, 2019	LSTM, MLP

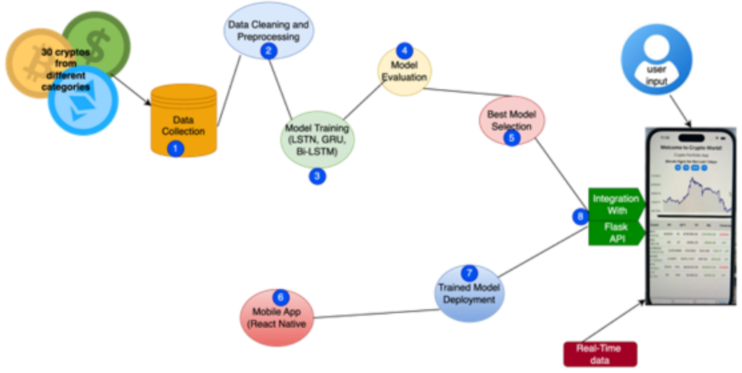
Project Overview

CryptoProphet project built a reliable app to fill the critical gap in cryptocurrency trading by providing future price prediction and integrated with portfolio app

The general approach is:

- **Selecting three (3) deep learning models**
- **Selecting thirty (30) representative cryptocurrencies**
- **Training model for selected cryptos**
- **Selecting best model for each crypto**
- **Bilding React Native mobile app**
- **Building Flask API**
- **Integrating the trained model with mobile app**

Design



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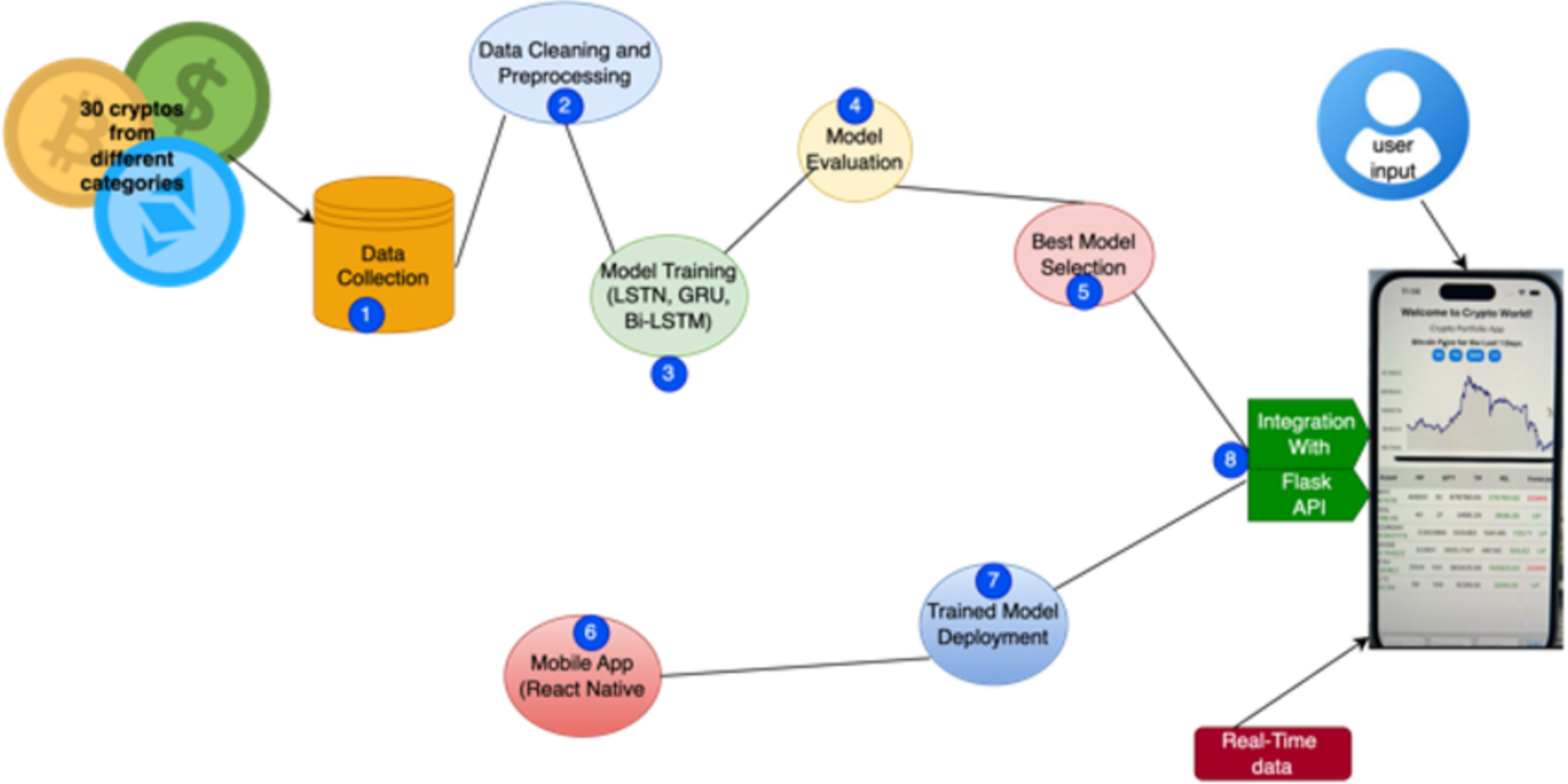
30 cryptos from different categories
Data Collection
1
Data Cleaning and Preprocessing
2
Model Training (LSTN, GRU, Bi-LSTM)
3
4
Model Evaluation
Best Model Selection
5
6
Mobile App (React Native
7
Trained Model Deployment
8
Integration With Flask API
user input
Welcome to Crypto World!
Real-Time data

Data Collection and Preprocessing

30 cryptocurrencies are selected to represent the crypto market for this portfolio project.

Selection of Cryptocurrency

Some of the categories for the selection of 30 cryptos are:

	Crypto	Symbol
1	Bitcoin	BTC
2	Tezos	XTZ
3	Decentraland	MANA
4	Ethereum	ETH
5	Siacoin	SC
6	Basic Attention Token	BAT
7	Decred	DCR
8	BNB	BNB
9	Solana	SOL
10	XRP	XRP
11	Dogecoin	DOGE
12	Cardano	ADA
13	Shiba Inu	SHIB
14	Avalanche	AVAX
15	Chainlink	LINK
16	TRON	TRX
17	Bitcoin Cash	BCH
18	Polygon	MATIC
19	Litecoin	LTC
20	Render	RNDR
21	Cosmos	ATOM
22	Stellar	XLM
23	Cronos	CRO
24	Monero	XMR
25	Stacks	STX
26	Maker	MKR
27	VeChain	VET
28	Fantom	FTM
29	Quant	QNT
30	Neo	NEO

- **High Market Capitalization**
- **Medium Market Capitalization**
- **Low Market Capitalization**
- **History of Launch**
- **Market Dominance**
- **Memes Coins**
- **Metaverse**
- **Gaming**
- **AI Crypto**
- **Smart Contracts**
- **Privacy Coins**

Data Collection

- Collected since 07/13/2010
- Historical price data collected for 30 cryptos using CmcScraper library from CoinMarketCap
- The collected data is preprocessed and normalized using MinMaxScaler from sklearn library
- The data is split into training and test set in which the last 365 days reserved for testing to evaluate the model's performance on recent data
- The normalized price data is then transformed into sequences of fixed length (lookback = 30 days) to capture temporal dependencies

	Crypto	Symbol	Market Cap	Dominance (%)	Date Since	Number of Observations
1	Bitcoin	BTC	$1.33 Trillion	62.77%	7/13/10	5060
2	Tezos	XTZ	$944.60 Million	0.04%	7/1/18	2150
3	Decentraland	MANA	$848.82 Million	0.04%	9/17/17	2437
4	Ethereum	ETH	$454.93 Billion	21.44%	8/7/15	3209
5	Siacoin	SC	$391.06 Million	0.02%	8/26/15	3189
6	Basic Attention Token	BAT	$362.93 Million	0.02%	6/1/17	2545
7	Decred	DCR	$332.54 Million	0.02%	2/10/16	3022
8	BNB	BNB	$87.73 Billion	4.13%	7/25/17	2491
9	Solana	SOL	$76.45 Billion	3.60%	4/10/20	1501
10	XRP	XRP	$28.68 Billion	1.35%	8/4/13	3942
11	Dogecoin	DOGE	$23.06 Billion	1.09%	12/15/13	3809
12	Cardano	ADA	$16.04 Billion	0.76%	10/1/17	2423
13	Shiba Inu	SHIB	$15.07 Billion	0.71%	8/1/20	1388
14	Avalanche	AVAX	$14.25 Billion	0.67%	7/13/20	1338
15	Chainlink	LINK	$10.85 Billion	0.51%	9/20/17	2430
16	TRON	TRX	$9.80 Billion	0.46%	9/13/17	2441
17	Bitcoin Cash	BCH	$9.01 Billion	0.42%	7/23/17	2493
18	Polygon	MATIC	$6.90 Billion	0.33%	4/28/19	1849
19	Litecoin	LTC	$6.22 Billion	0.29%	4/28/13	4040
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23	Cronos	CRO	$3.01 Billion	0.14%	12/14/18	1984
24	Monero	XMR	$2.74 Billion	0.13%	5/21/14	3651
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29	Quant	QNT	$1.09 Billion	0.05%	8/10/18	2110
30	Neo	NEO	$1.03 Billion	0.05%	9/9/16	2810

Data Preprocessing

- **Data underwent a rigorous cleaning process to ensure its accuracy and reliability**
- **Missing were addressed**
- **The cleaned data was then structured into a unified format**
- **The data was trained on the three model**

```
# List of cryptocurrency symbols
cryptos = ["BTC", "ETH", "BNB", "ADA", "SOL", "XRP", "LTC","LINK", "DOGE", "SHIB",
           "MANA", "VET", "XMR", "BCH", "AVAX", "TRX", "MATIC", "CRO", "RNDR", "XTZ",
           "BAT", "SC", "FTM","DCR","MKR", "ATOM","STX", "XLM", "QNT", "NEO"]

lookback = 30
test_days = 365

def get_historical_data(crypto_symbol, start_date='03-01-2009', end_date='25-05-2024'):
    scraper = CmcScraper(crypto_symbol, start_date, end_date)
    df = scraper.get_dataframe()
    df['Close'] = df['Close'].astype(float)
    return df

def prepare_data(df, lookback, test_days):
    data = df[['Close']].values

    train_data = data[:-test_days]
    test_data = data[-test_days:]

    scaler = MinMaxScaler()
    train_scaled = scaler.fit_transform(train_data)
    test_scaled = scaler.transform(test_data)

    def create_sequences(data, lookback):
        X, y = [], []
        for i in range(len(data) - lookback - 1):
            X.append(data[i:i + lookback])
            y.append(data[i + lookback + 1])
        return np.array(X), np.array(y)

    X_train, y_train = create_sequences(train_scaled, lookback)
    X_test, y_test = create_sequences(test_scaled, lookback)

    return X_train, X_test, y_train, y_test, scaler
```

```
def build_and_train_model(model_type, X_train, y_train, X_val, y_val):
    model = Sequential()
    if model_type == 'LSTM':
        model.add(LSTM(50, activation='tanh', return_sequences=False, input_shape=(lookback, 1)))
    elif model_type == 'GRU':
        model.add(GRU(50, activation='tanh', return_sequences=False, input_shape=(lookback, 1)))
    elif model_type == 'Bi-LSTM':
        model.add(Bidirectional(LSTM(50, activation='tanh', return_sequences=False), input_shape=(lookback, 1)))
    model.add(Dropout(0.1))
    model.add(Dense(1))
    model.compile(optimizer='adam', loss='mse')

    early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)

    history = model.fit(X_train, y_train, epochs=100, batch_size=32, validation_data=(X_val, y_val),
                        verbose=1, callbacks=[early_stopping])

    val_loss = min(history.history['val_loss'])
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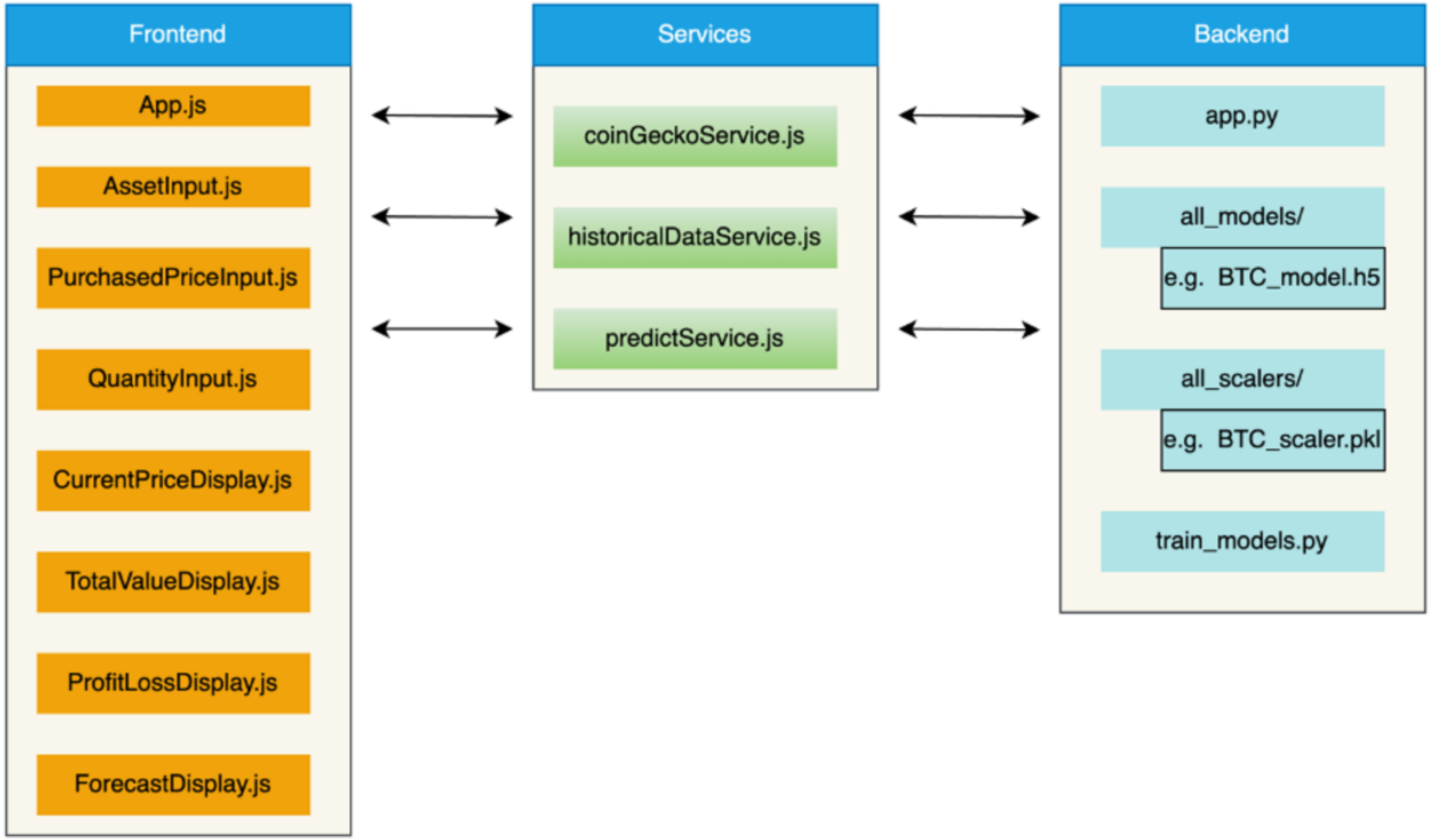
Technical Architecture of the App



React Native

AssetInput.js/:
- user input component

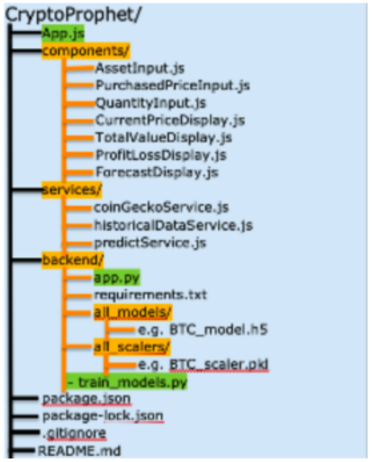
PurchasedPriceInput.js/:
- purchased user input

QuantityInput.js/:
- quantity user input

all_models/:
- directory to store all the trained models

all_scalers/:
- directory to store the scalers used for data preprocessing

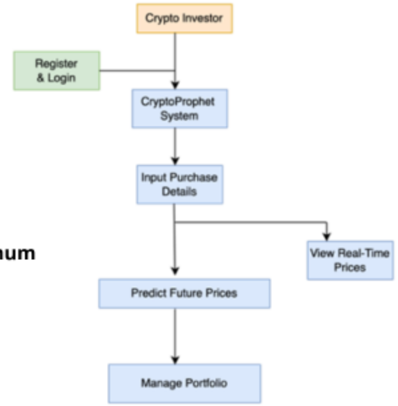
app.py:
- the main Flask application file

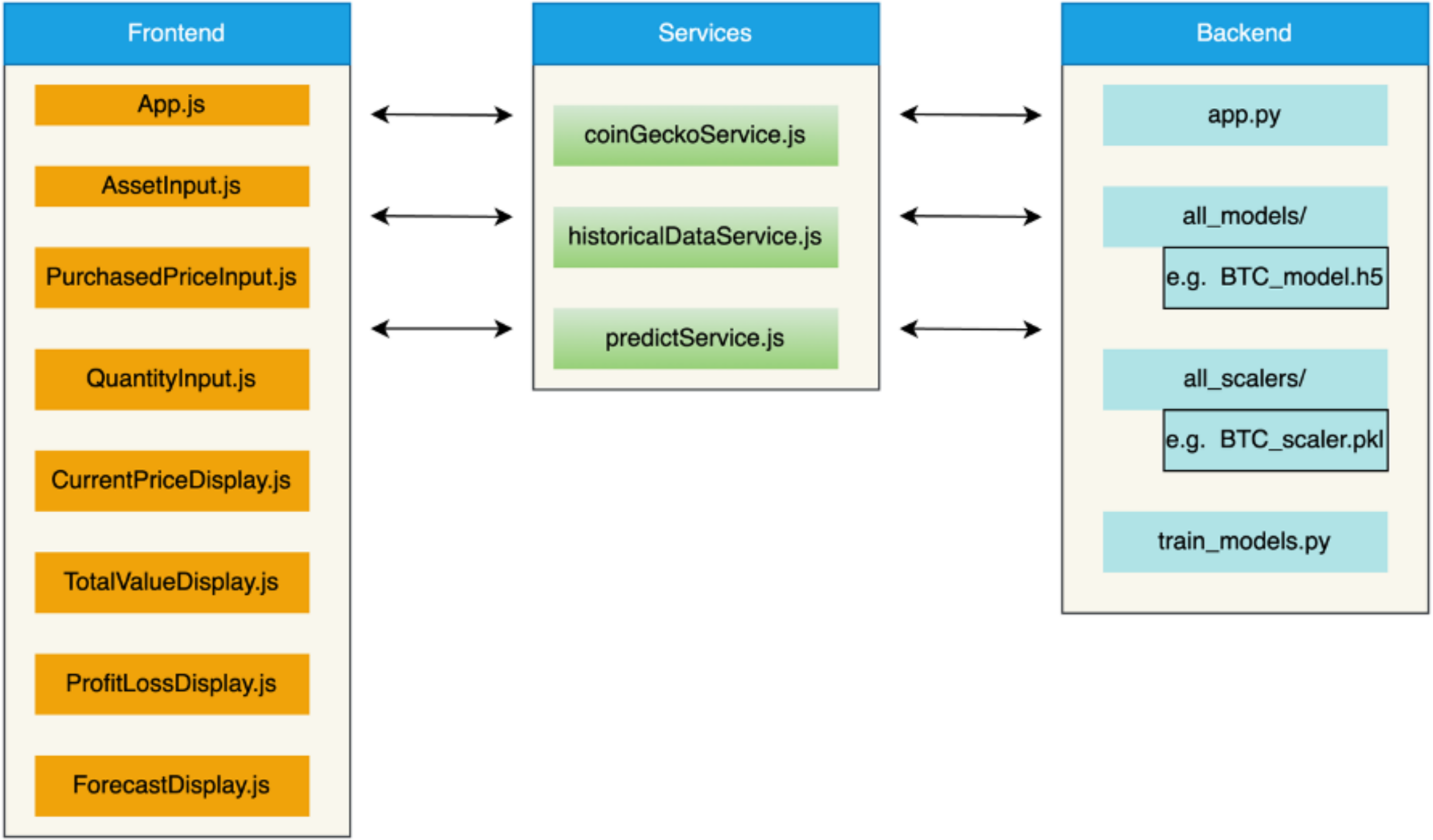


Use of CryptoProphet

CrypptoProphet portfolio app enables users to:

- **Forcusting crypto prices**
- **Manage their cryptocurrency investments**
- **Track their investmnets**
- **Make informed decisions**
- **Optimize their portfolios for maximum profitability**
- **Leveraging real-time data and predictive analytics**




Frontend
App.js
AssetInput.js
PurchasedPriceInput.js
QuantityInput.js
CurrentPriceDisplay.js
TotalValueDisplay.js
ProfitLossDisplay.js
ForecastDisplay.js
Services
coinGeckoService.js
historicalDataService.js
predictService.js
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app.py
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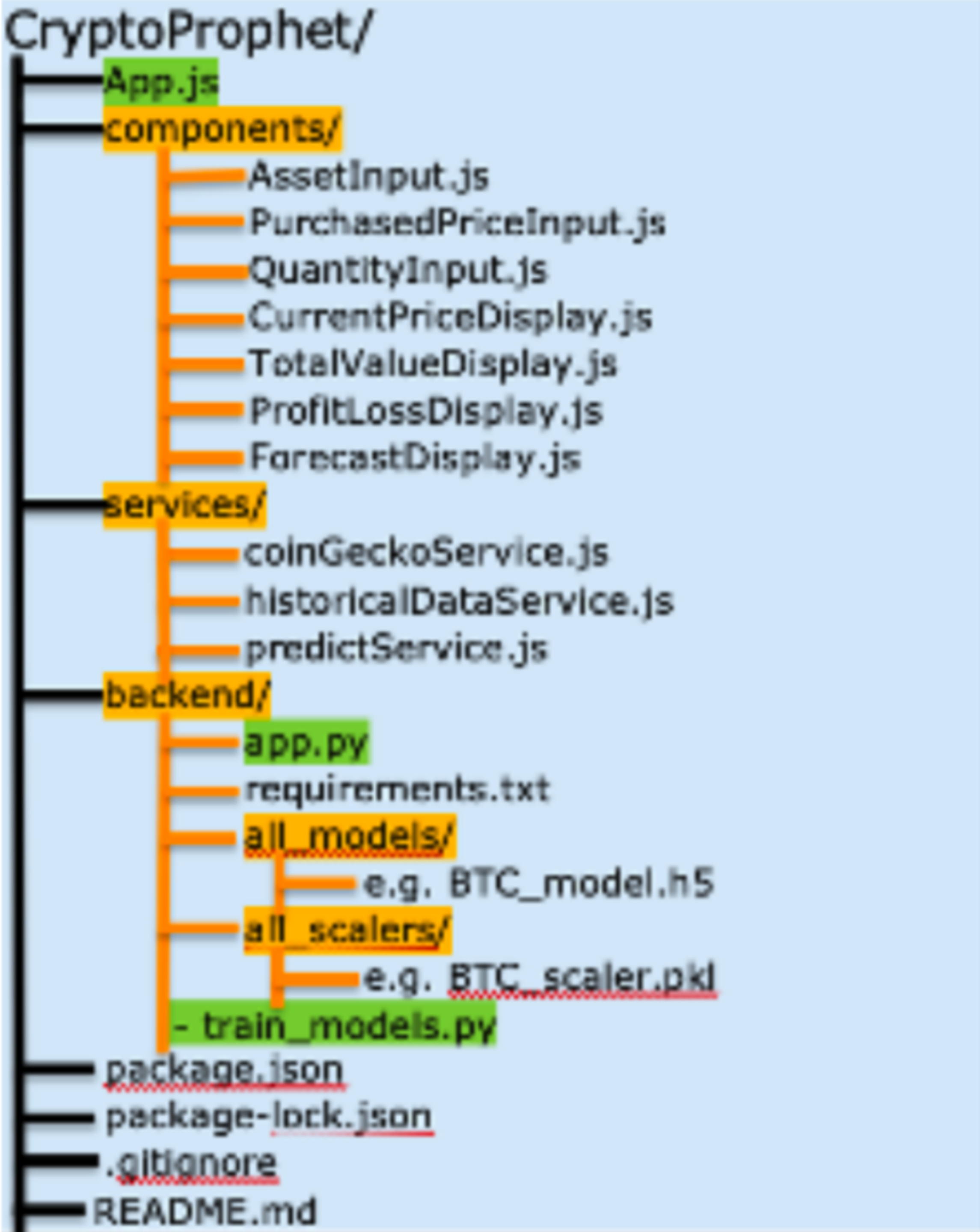

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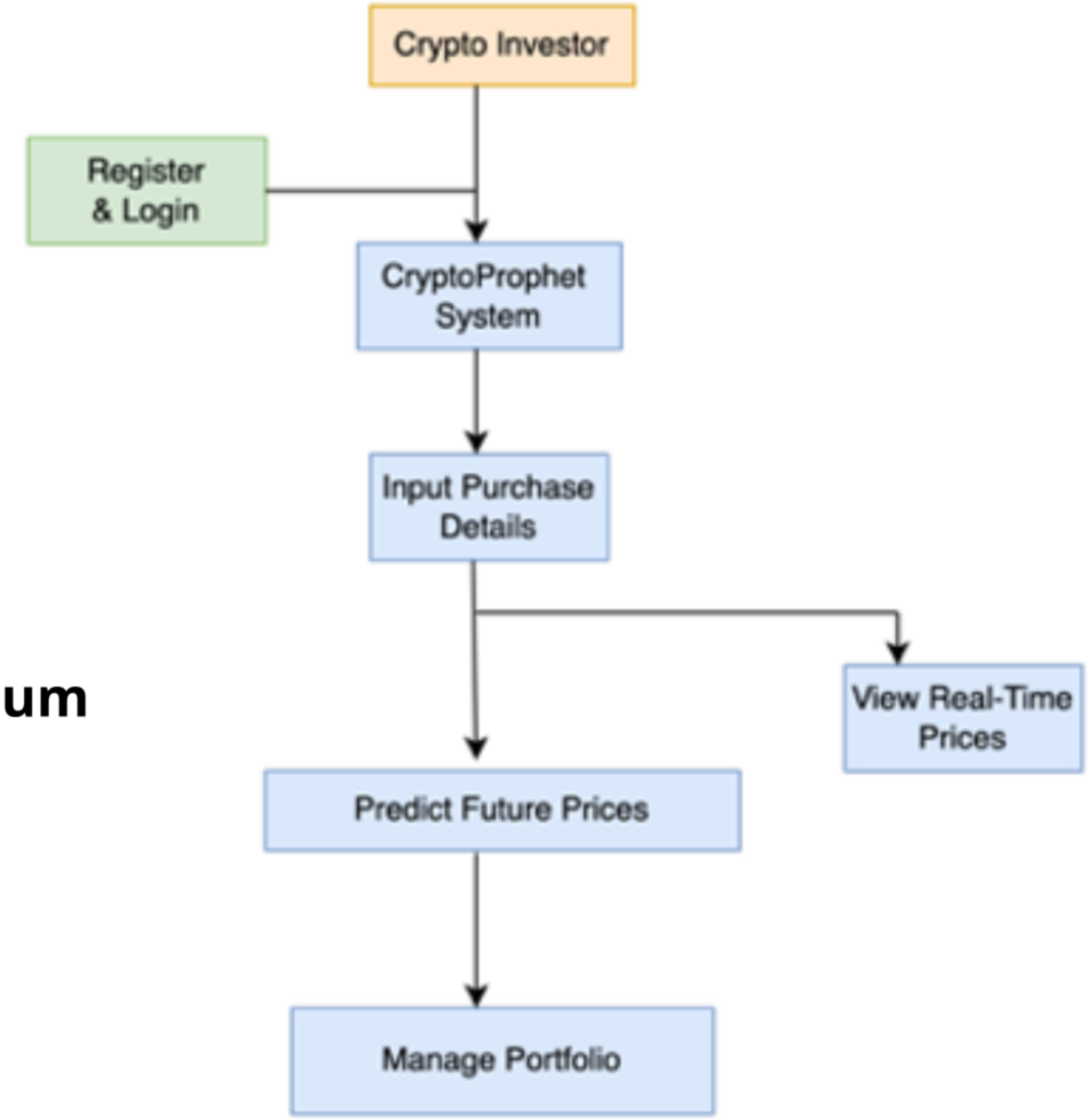

Data Analysis

Data Analysis ...

- High market and dominance crypto are less volatile compared to smaller crypto (BTC, ETH)
- Smaller market cap and dominance more volatility and higher risk (XTZ, BAT)
- The number of observation can directly impact the accuracy of the training model
- Newer crypto with fewer observation might need more sophisticated algorithms to achieve comparable predictive performance

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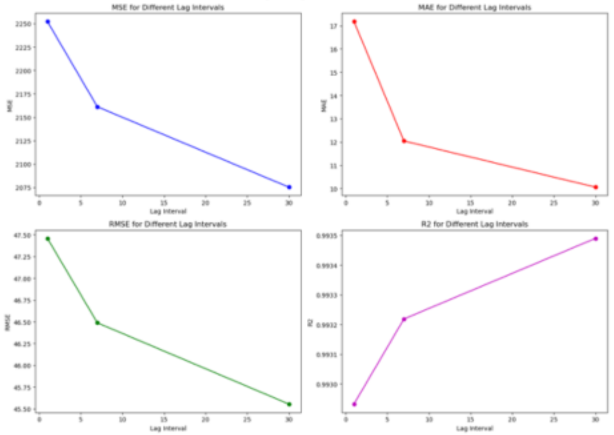
25	Stacks	STX	$2.68 Billion	0.13%	10/28/19	1666
26	Maker	MKR	$2.56 Billion	0.12%	1/29/17	2390
27	VeChain	VET	$2.47 Billion	0.12%	8/3/18	2117
28	Fantom	FTM	$2.23 Billion	0.11%	10/30/18	2029
29	Quant	QNT	$1.09 Billion	0.05%	8/10/18	2110
30	Neo	NEO	$1.03 Billion	0.05%	9/9/16	2810

Data Analysis ...

```python
# evaluating the optimum lookback period
lookback_values = [1, 7, 30]
performance_metrics_df = evaluate_lag_intervals(df, lookback_values)
```

lookback: refers to number of previous time steps used by a predictive model to make future predictions.

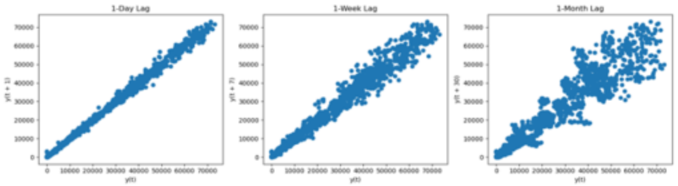
- **It's historical data that the model considers to forecast the next value in a time series**
- **30-day lookback period allows the model to better capture the underlying trends and variability in crypto prices**



Data Analysis ...

- **Strong linear relationship between the prvious time y(t) and the next time y(t + 1)**
- **It indicates a high autocorrelation at a one-day interval**
- **This lag plot suggest that the price of the cryptocurrency on any given day is highly predictive of its previous price.**

Lag Plots



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- **Pairwise correlations between the daily returns of various cryptocurrencies**
- **Correlation value between -1 to 1**
  - **1 -> strong +ve correlation**
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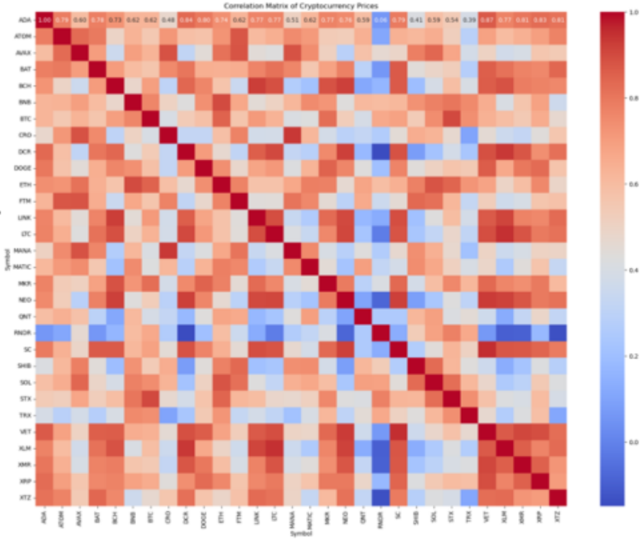
- **Understanding this correlations is crucial for the predictive modeling and portfolio management**



Data Analysis ...

- High market and dominance crypto are less volatile compared to smaller crypto (BTC, ETH)
- Smaller market cap and dominance more volatility and higher risk (XTZ, BAT)
- The number of obervation can directly impact the accuracy of the training model
- Newer crypto with fewer observation might need more sophisticated algorithms to achieve comparable predictive performance

	Crypto	Symbol	Market Cap	Dominance (%)	Date Since	Number of Observations
1	Bitcoin	BTC	$1.33 Trillion	62.77%	7/13/10	5060
2	Tezos	XTZ	$944.60 Million	0.04%	7/1/18	2150
3	Decentraland	MANA	$848.82 Million	0.04%	9/17/17	2437
4	Ethereum	ETH	$454.93 Billion	21.44%	8/7/15	3209
5	Siacoin	SC	$391.06 Million	0.02%	8/26/15	3189
6	Basic Attention Token	BAT	$362.93 Million	0.02%	6/1/17	2545
7	Decred	DCR	$332.54 Million	0.02%	2/10/16	3022
8	BNB	BNB	$87.73 Billion	4.13%	7/25/17	2491
9	Solana	SOL	$76.45 Billion	3.60%	4/10/20	1501
10	XRP	XRP	$28.68 Billion	1.35%	8/4/13	3942
11	Dogecoin	DOGE	$23.06 Billion	1.09%	12/15/13	3809
12	Cardano	ADA	$16.04 Billion	0.76%	10/1/17	2423
13	Shiba Inu	SHIB	$15.07 Billion	0.71%	8/1/20	1388
14	Avalanche	AVAX	$14.25 Billion	0.67%	7/13/20	1338
15	Chainlink	LINK	$10.85 Billion	0.51%	9/20/17	2430
16	TRON	TRX	$9.80 Billion	0.46%	9/13/17	2441
17	Bitcoin Cash	BCH	$9.01 Billion	0.42%	7/23/17	2493
18	Polygon	MATIC	$6.90 Billion	0.33%	4/28/19	1849
19	Litecoin	LTC	$6.22 Billion	0.29%	4/28/13	4040
20	Render	RNDR	$3.92 Billion	0.18%	6/11/20	1439
21	Cosmos	ATOM	$3.27 Billion	0.15%	3/14/19	1894
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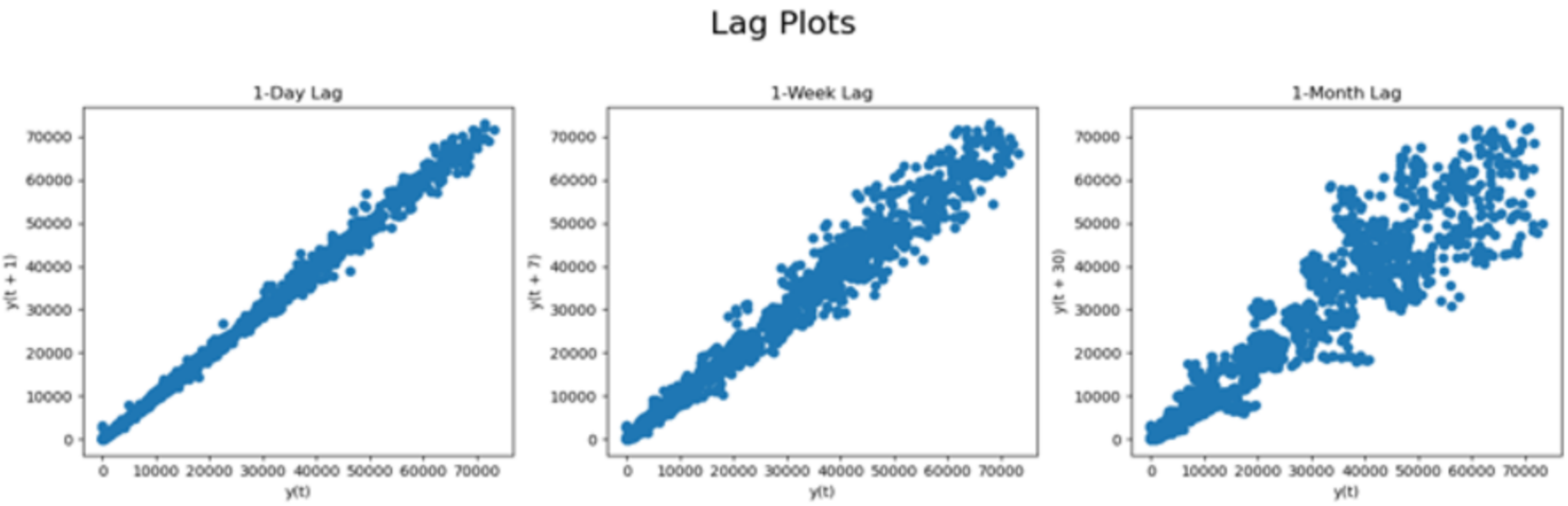

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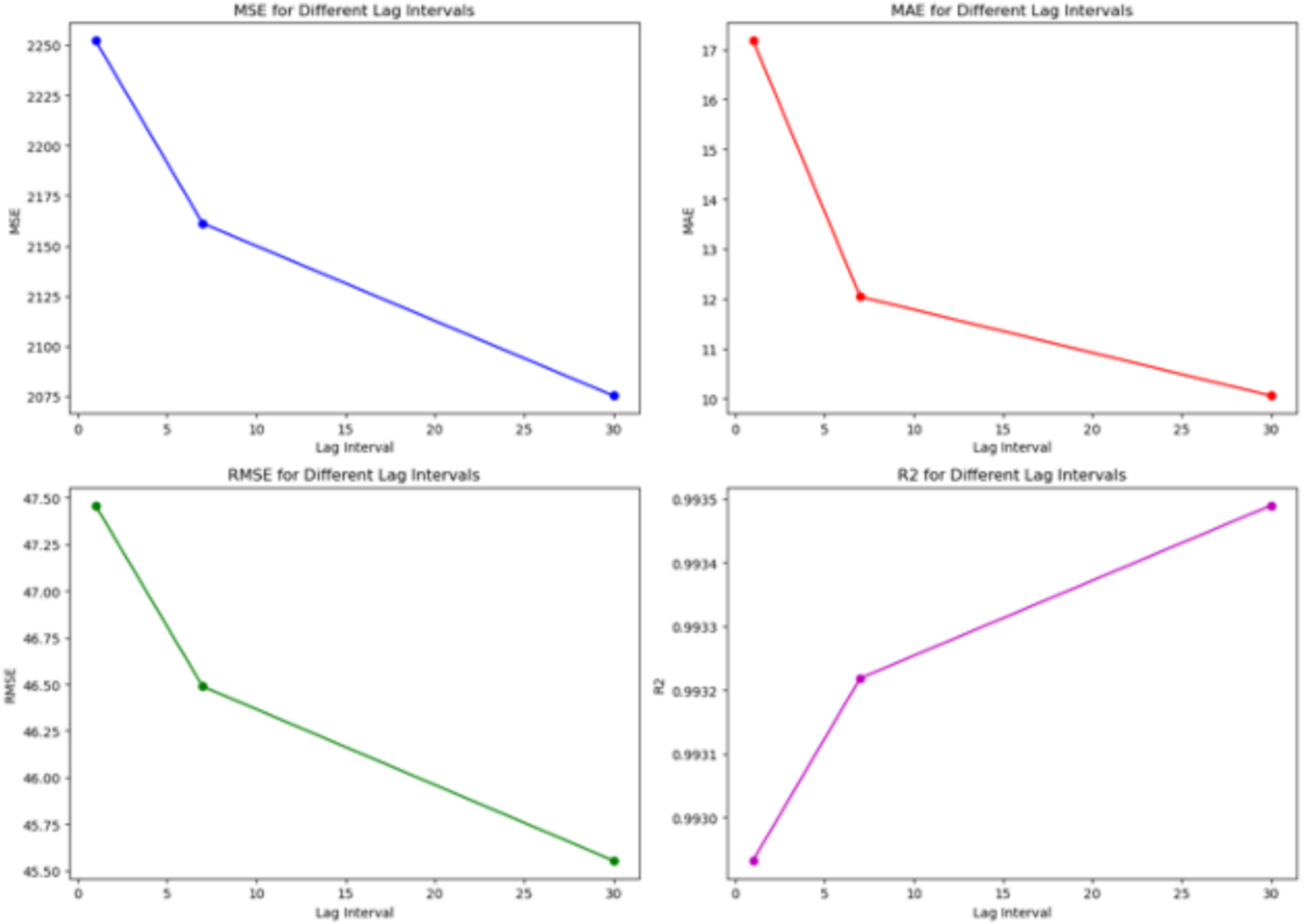

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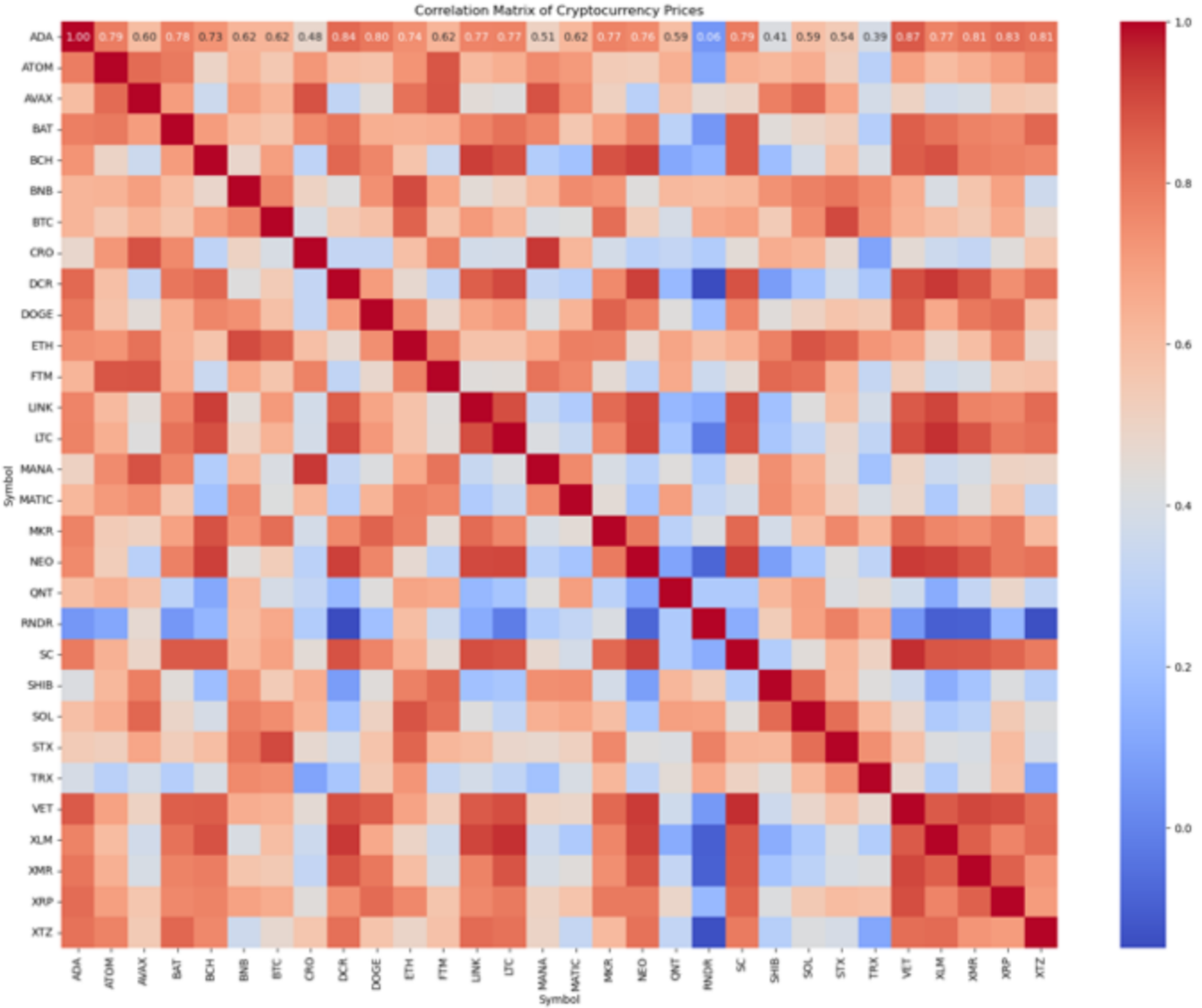

Model Selection and Training

- Time-series data is a sequence of data points collected or recorded at specific time intervals
- It is used to track changes over time and is essential for various analytics tasks, including forecasting and trend analysis
- Cryptocurrency data are recorded at regular intervals, such as every minute, hour, day, or month which is crucial for analyzing trends and making predictions
- The value of a cryptocurrency at a given time point often dependent on its previous values

Model Selection ...

The recommended deep learning model for time-series forecasting like cryptocurrency are:

- Long Short-Term Memory (LSTM)
- Gated Recurrent Unit (GRU)
- Bidirectional LSTM (Bi-LSTM)

Some of main reason for these recommended models are:

- Handling Long-Term dependencies
- Avoiding Vanishing Gradient Problem
- Flexibility
- Efficiency
- Enhanced Accuracy
- Flexibility and Versatility

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Individualized Model Selection (IMS)

- IMS is a strategy where the best-performing model is selected for each cryptocurrency individually, rather than applying a single model type or ensemble across all cryptocurrencies.
- This approach ensures that the model used for prediction is tailored to the unique characteristics of each cryptocurrency's market behavior

Comparison with Other Methods

Approach	Strength	Weaknesses	Why IMS is Better
Single Model	Simplicity and consistency across assets.	May not perform well for all cryptocurrencies due to varying behaviors.	IMS adapts to the specific needs of each cryptocurrency, improving overall prediction quality.
Ensemble Models	Robust and often more accurate in diverse datasets.	Computationally expensive, less interpretable, and may dilute the performance of the best-suited model.	IMS avoids computational complexity and focuses on the strongest model for each asset.
IMS Strategy	Tailored predictions, high accuracy, computationally efficient, and interpretable.	Requires additional effort in training and evaluation for each cryptocurrency.	Despite the effort, IMS ensures optimal predictions for each cryptocurrency, maximizing utility.

Why IMS?

1. Heterogeneity in Crypto Markets:
   - Crypto exhibit diverse price patterns and market behaviours due to differences in market capitalization, trading volume, and investor interest
2. Limitations of Single Models:
   - Single models may excel for some crypto but underperform for others
3. Drawbacks of Esembles:
   - Ensembles combine predictions from multiple models, which can dilute the performance benefits of an individual model that's well-suited for a specific crypto
4. Precision and Customization:
   - IMS allows for the selection of the best model for each crypto based on performance metrics, resulting in more precise and reliable predictions.

How IMS works

1. Training Multiple Models:
   - For each cryptocurrency, three types of deep models are trained: LSTM, GRU, Bi-LSTM.
2. Evaluating Performance:
   - Models are evaluated using a comprehensive set of metrics, including:
     - Mean Absolute Error (MAE)
     - Mean Squared Error (MSE)
     - Root Mean Squared Error (MAPE)
     - Coefficient of Determination (R2)
3. Selecting the Best Model:
   - Based on the evalution, the model with the best performance for each crypto is selected
4. Implementing in the App:
   - IMS ensures that when a user selects a crypto, the app dynamically loads the pre-selected model for that asset to provide the most accurate predictions.

Advantages of IMS over Other Methods

1. Improved Accuracy:
   - By using the best-suited model for each crypto, IMS achieves higher predictive accuracy compared to applying a single model or ensemble across all assets.
2. Efficiency:
   - Unlike ensemble, IMS avoids the computational overhead of combining multiple model outputs during inference, making it faster and more resource-efficient.
3. Interpretability:
   - IMS provides clarity about why a particular model was chosen for a crypto, enhancing trust and transparency for users.
4. Adaptability:
   - IMS is flexible enough to integrate new models or refine selection criteria as market dynamics evolve.

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Evaluation Metrics and Model Performance

Performance metrics evaluation of the predicted and actual values.

- **Mean Absolute Error (MAE)**
- **Mean Squared Error (MSE)**
- **Root Mean Squared Error (RMSE)**
- **R-squared (R2)**

- **High R2 values indicates that the model can effectively capture and pridict the price movement, which is accurate prediction**
- **Overall, these evaluations ensures that the app provides reliable and actionable predictions**

crypto	model_type	MAE	MSE	RMSE	MAPE (%)	R2
BTC	GRU	1146.0229321972000	2916420.6418867500	1707.75309746074	2.52606224546220	0.9869227677820090
ETH	GRU	66.78026471892760	9743.943418532300	98.71141483401150	2.65501797144997O	0.9781979175542160
BNB	GRU	11.057782877637000	332.1959967684940	18.226244724805300	2.8557689672004600	0.9828556751790460
ADA	GRU	0.017889472364757700	0.000758691206405504	0.027544349809089800	3.8602479463543400	0.9666757555366180
SOL	GRU	4.854035250080750	58.67239108778780	7.659790538114460	5.864999796478180	0.9812088934695300
XRP	GRU	0.018729255525508200	0.001134329845508730	0.033679813620457200	3.1595227463612000	0.7785169654025020
LTC	Bi-LSTM	2.923520203379290	19.37832613392660	4.402082022625950	3.6754623549424100	0.863105585084624
LINK	GRU	0.6012970016320770	0.7197413603101720	0.8483757188358070	4.7272386802480700	0.9692517604859360
DOGE	GRU	0.004610810178388240	6.83605849443954E-05	0.008268046017312400	4.024969471139600	0.9581056503990430
SHIB	GRU	7.19919392859641E-07	2.92902939802795E-12	1.7114407375156E-06	4.38192208755231O	0.9542085456060000
MANA	GRU	0.023106293994709400	0.0010679181385870700	0.032679016793457400	5.0594217310575700	0.913702047802004
VET	GRU	0.0012468831566193800	3.7655912806984E-06	0.0019405131488084300	4.1377853096424000	0.967659690083565
XMR	GRU	3.6116782307255500	33.98404643104450	5.829583727080730	2.52530454629472O	0.873236259162985O
BCH	GRU	18.171766180874800	1023.9637527871900	31.999433632287800	5.493657568017290	0.9271112351005340
AVAX	GRU	1.49466274076195	5.50489677241659	2.3462516430290700	5.070813859164450	0.9751543555680090
TRX	GRU	0.00454479766252581	3.05800892760126E-05	0.0055299266971644900	4.1691896982153700	0.9197688011755720
MATIC	GRU	0.03302981351632030	0.0020522104373780300	0.045301329311379200	4.2246037889708000	0.9268865155650640
CRO	GRU	0.0034410429478797300	3.31033284283272E-05	0.005753549202738010	3.51625713572838O	0.9704685576649470
RNDR	GRU	0.33958221439565800	0.35661467712877600	0.5971722340571240	6.00182941944931	0.9662588770692870
XTZ	GRU	0.037505869275487300	0.0028733952662834600	0.05360406016603090	3.8557211895831400	0.9351222550756140
BAT	LSTM	0.009542970976180780	0.00018828176915124700	0.013721580417402600	4.0168782335176900	0.9123285366684590
SC	GRU	0.0004354427850027760	8.9422452394013E-07	0.0009456344557703730	5.83763196472438	0.9122506107237390
FTM	LSTM	0.02795194253367830	0.002380025628127990	0.04878550633259830	5.628912505142950	0.9591150057339260
DCR	GRU	0.9146203903271100	1.7346623507345100	1.317065811087100	5.095647665838270	0.9068616632997060
MKR	GRU	91.49046257125120	19907.86463745810	141.0952325114430	4.762330713780950	0.9662447712515940
ATOM	GRU	0.39836987342936500	0.28695069220600900	0.5356777876727850	4.322235201654790	0.9012193019140290
STX	GRU	0.09799387577272990	0.02801945174424010	0.16739011841874100	5.788644870104680	0.9702536203679250
XLM	LSTM	0.0043210773701783	4.73242277575921E-05	0.006879260698475680	3.472503977705360	0.7462423785002910
QNT	GRU	4.0850830704828800	31.903498917999600	5.64831823802445	3.7309829481302600	0.7953354456345730
NEO	Bi-LSTM	0.5653299034222750	0.8393385753969280	0.9161542312279790	4.547300440034160	0.9370619607352130

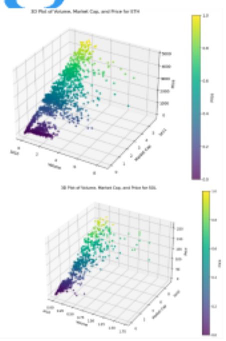
Results: Predictive Accuracy and Insights

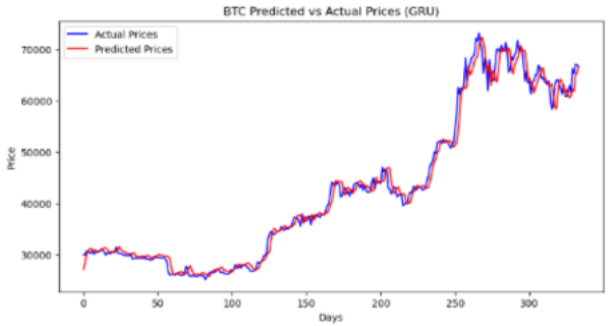
- The predicted price closely follow the actual prices over time
- This indicates that the model performs well in capturing the overall trend and fluctuations
- The visualizations and performance metrics underscore the predictive model's ability to forecast crypto price accurately.

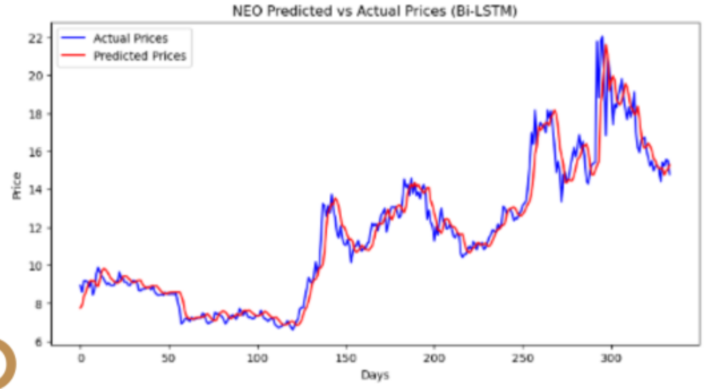
Results …

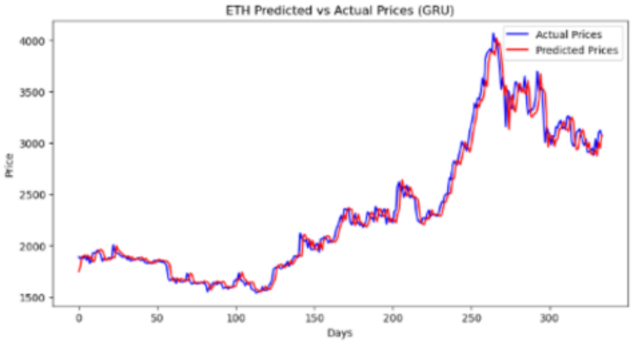
The 3D scatter pots highlight the relationships between trading volume, market capitalization, and price for crypto price predictions.

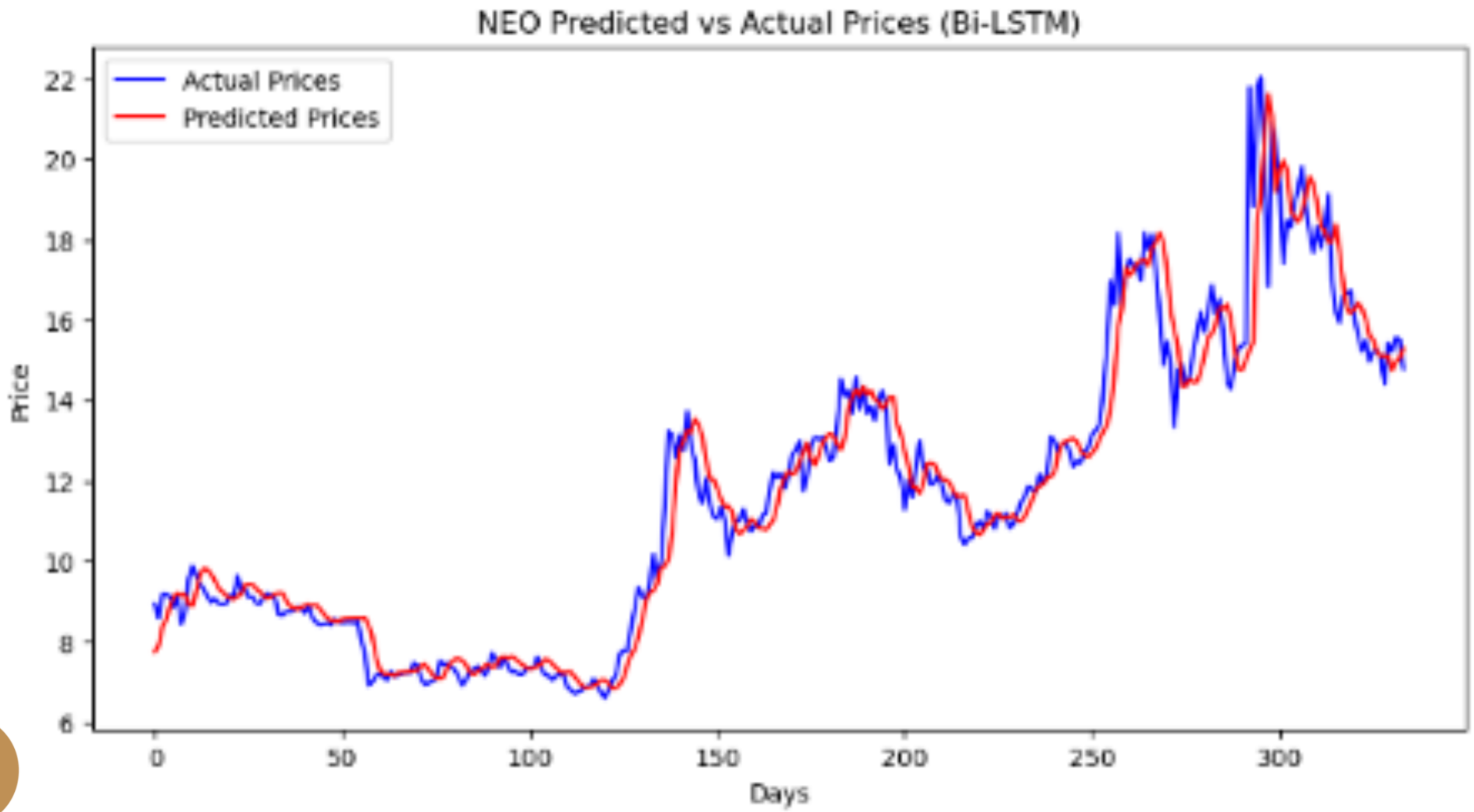
It indicates that the predictions accuracy will be inhanced by incorporating these additional features into the model.

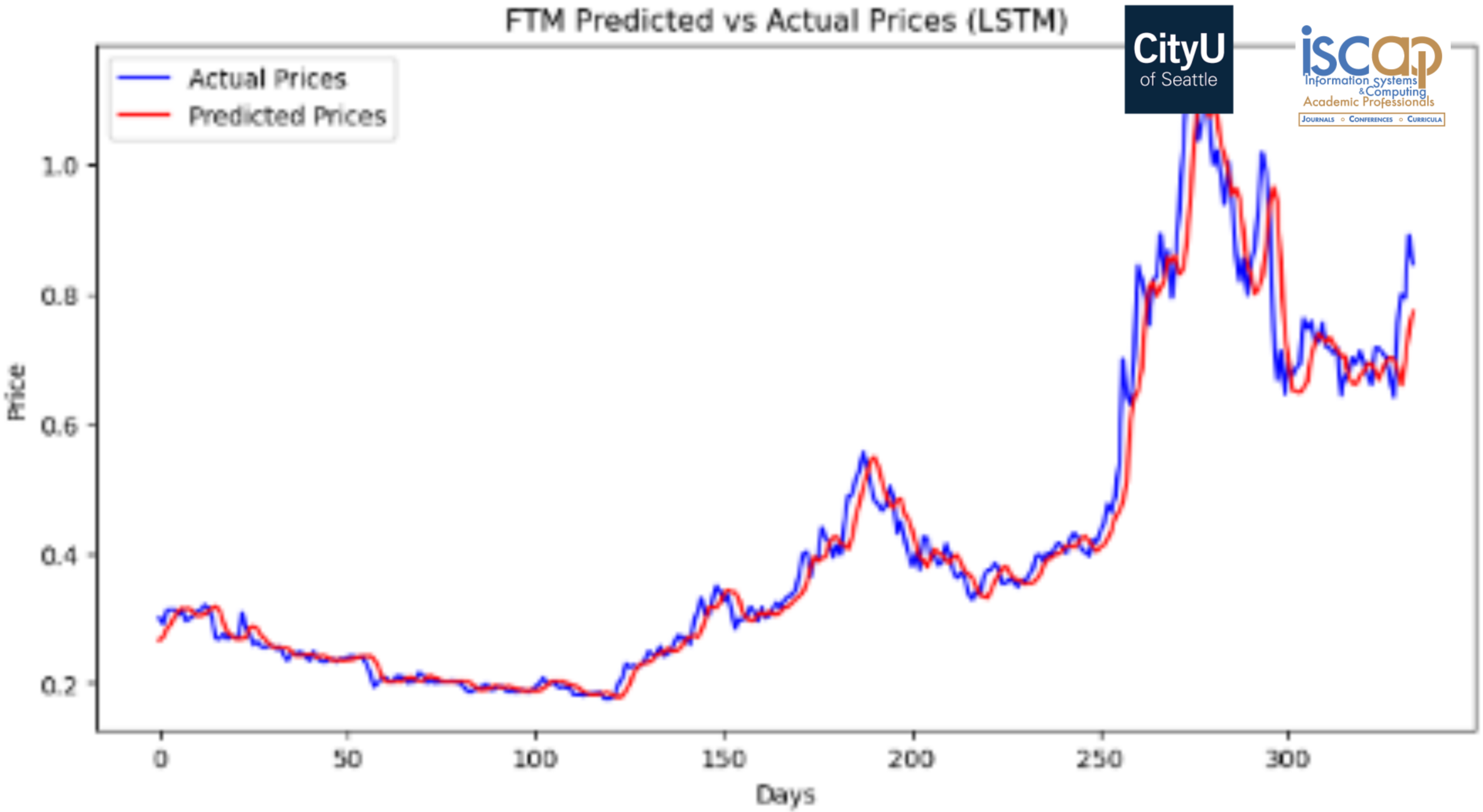


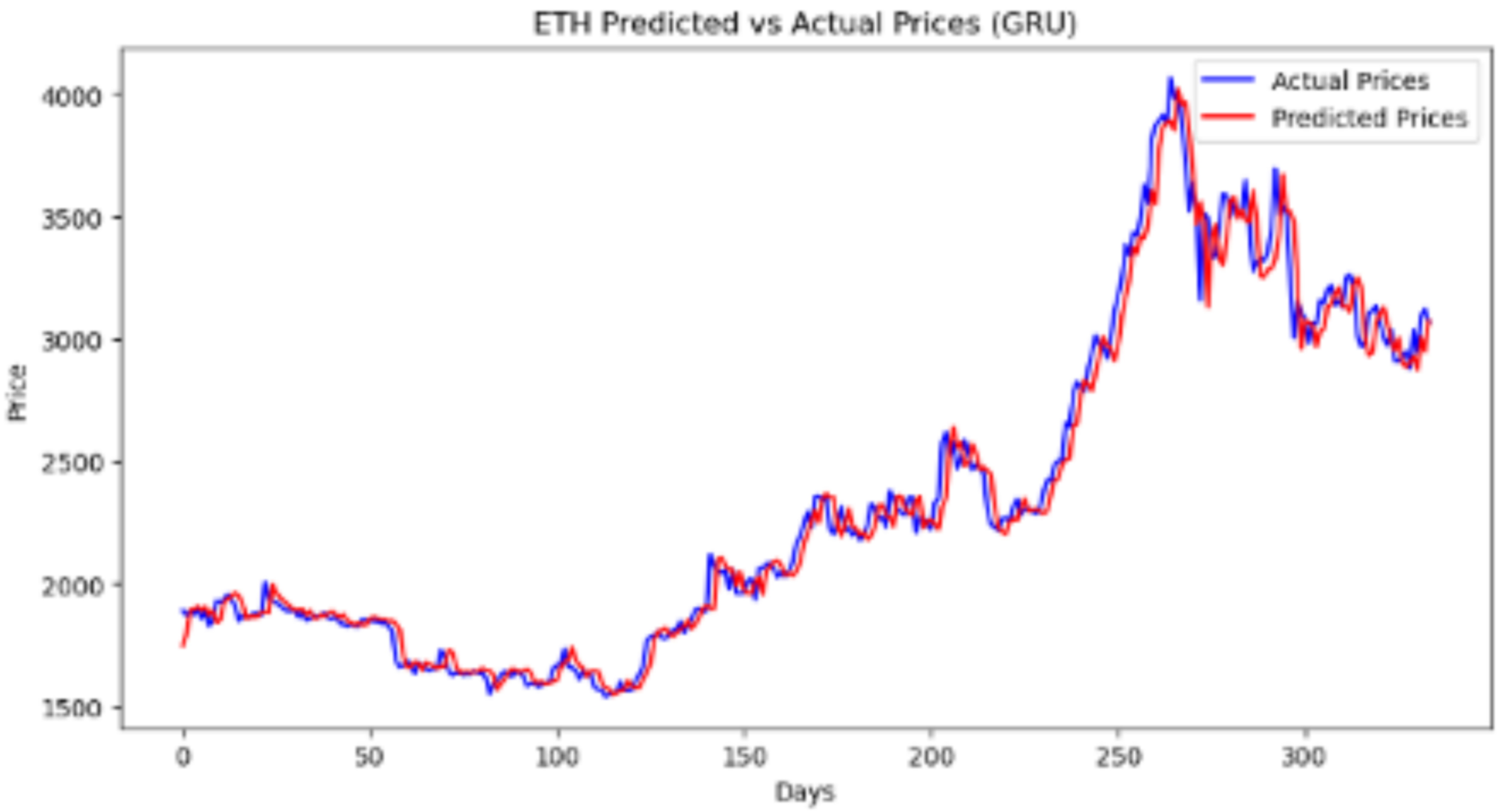


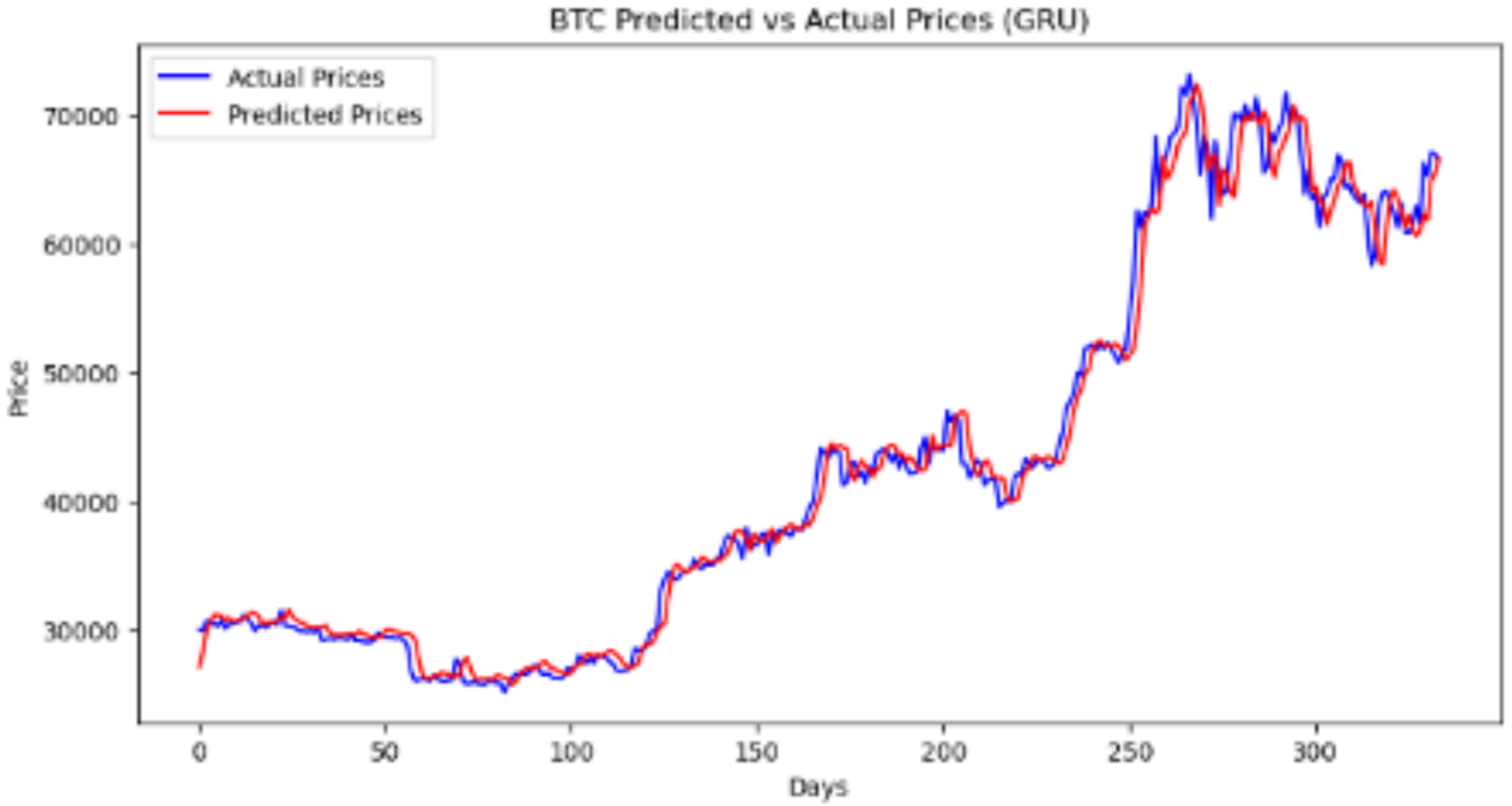





NEO Predicted vs Actual Prices (Bi-LSTM)
Actual Prices
Predicted Prices
Price
Days
22
20
18
16
14
12
10
8
6
0
50
100
150
200
250
300


FTM Predicted vs Actual Prices (LSTM)
Actual Prices
Predicted Prices
Price
Days
1.0
0.8
0.6
0.4
0.2
0
50
100
150
200
250
300
CityU of Seattle
iscap
Information Systems &Computing Academic Professionals
Journals ◦ Conferences ◦ Curricula


ETH Predicted vs Actual Prices (GRU)
Actual Prices
Predicted Prices
Price
Days
4000
3500
3000
2500
2000
1500
0
50
100
150
200
250
300


BTC Predicted vs Actual Prices (GRU)
Actual Prices
Predicted Prices
70000
60000
50000
40000
30000
Price
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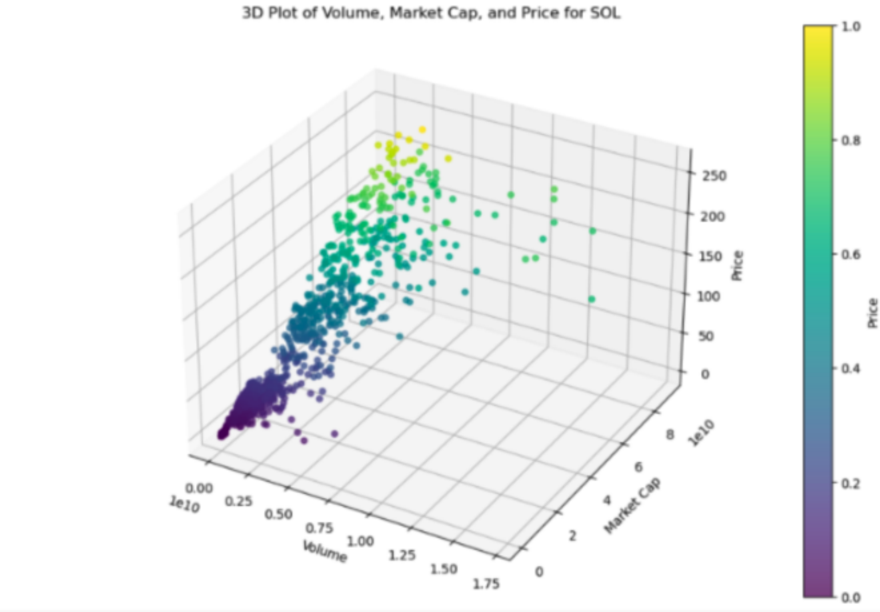

Conclusion

- CryptoProphet app addresses the inherent volatility and unpredictability of the cryptocurrency market, which leads to significant financial losses for investors
- CryptoProphet app provides reliable price forecasts for a range of cryptocurrencies, helping investors make informed decisions to minimize risks and maximize profits
- The integration of the predictive model into a mobile application ensures that users can easily access real-time price predictive and other crucial market information.

Future Work

- Incorporating Sentiment Analysis
- Incorporating additional features
- Enhancing the model's adaptability to suddent market changes

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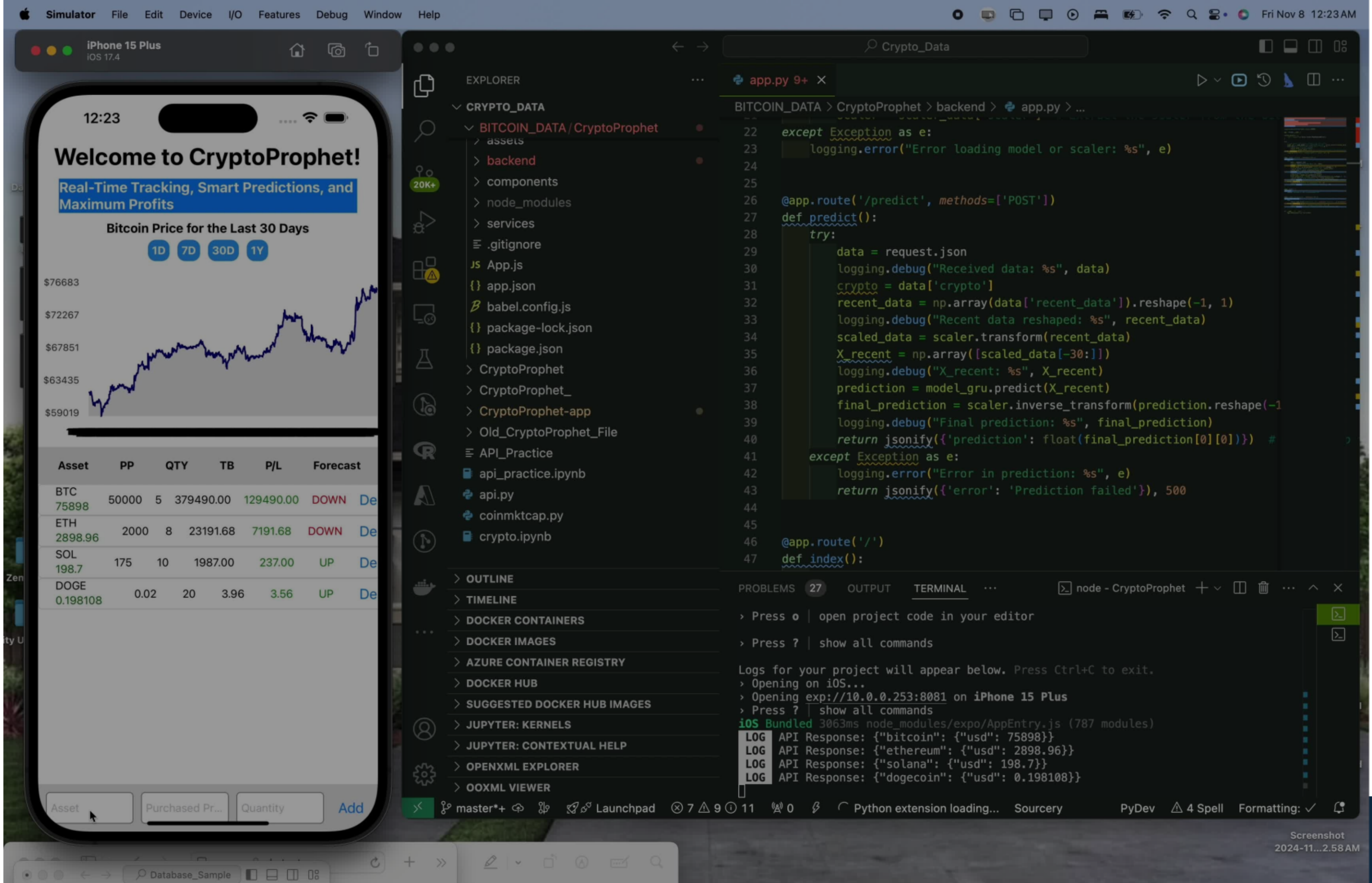

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iOS 17.4
12:23
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Bitcoin Price for the Last 30 Days
1D 7D 30D 1Y
$76683
$72267
$67851
$63435
$59019
Asset PP QTY TB P/L Forecast
BTC 75898 50000 5 379490.00 129490.00 DOWN
ETH 2898.96 2000 8 23191.68 7191.68 DOWN
SOL 198.7 175 10 1987.00 237.00 UP
DOGE 0.198108 0.02 20 3.96 3.56 UP
Asset
Purchased Pr...
Quantity
Add
Crypto_Data
EXPLORER
CRYPTO_DATA
BITCOIN_DATA / CryptoProphet
assets
backend
components
node_modules
services
.gitignore
App.js
app.json
babel.config.js
package-lock.json
package.json
CryptoProphet
CryptoProphet_
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Old_CryptoProphet_File
API_Practice
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coinmktcap.py
crypto.ipynb
OUTLINE
TIMELINE
DOCKER CONTAINERS
DOCKER IMAGES
AZURE CONTAINER REGISTRY
DOCKER HUB
SUGGESTED DOCKER HUB IMAGES
JUPYTER: KERNELS
JUPYTER: CONTEXTUAL HELP
OPENXML EXPLORER
OOXML VIEWER
app.py 9+
BITCOIN_DATA > CryptoProphet > backend > app.py > ...
except Exception as e:
logging.error("Error loading model or scaler: %s", e)
@app.route('/predict', methods=['POST'])
def predict():
try:
data = request.json
logging.debug("Received data: %s", data)
crypto = data['crypto']
recent_data = np.array(data['recent_data']).reshape(-1, 1)
logging.debug("Recent data reshaped: %s", recent_data)
scaled_data = scaler.transform(recent_data)
X_recent = np.array([scaled_data[-30:]])
logging.debug("X_recent: %s", X_recent)
prediction = model_gru.predict(X_recent)
final_prediction = scaler.inverse_transform(prediction.reshape(-1
logging.debug("Final prediction: %s", final_prediction)
return jsonify({'prediction': float(final_prediction[0][0])})
except Exception as e:
logging.error("Error in prediction: %s", e)
return jsonify({'error': 'Prediction failed'}), 500
@app.route('/')
def index():
PROBLEMS 27 OUTPUT TERMINAL
node - CryptoProphet
› Press o │ open project code in your editor
› Press ? │ show all commands
Logs for your project will appear below. Press Ctrl+C to exit.
› Opening on iOS...
› Opening exp://10.0.0.253:8081 on iPhone 15 Plus
› Press ? │ show all commands
iOS Bundled 3063ms node_modules/expo/AppEntry.js (787 modules)
LOG API Response: {"bitcoin": {"usd": 75898}}
LOG API Response: {"ethereum": {"usd": 2898.96}}
LOG API Response: {"solana": {"usd": 198.7}}
LOG API Response: {"dogecoin": {"usd": 0.198108}}
master*+ Launchpad 7 9 11 0 Python extension loading... Sourcery PyDev 4 Spell Formatting: ✓
Screenshot 2024-11...2.58 AM

Key References

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