Crypto Currency Price Predictor

A

Project Report

Submitted for the partial fulfilment

of B.Tech Degree

in

COMPUTER SCIENCE & ENGINEERING

by

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Contents

Declaration

We hereby declare that this submission is our work and that, to the best of our belief and knowledge, it contains no material previously published or written by another person or material which to a substantial error has been accepted for the award of any degree or diploma of university or another institute of higher learning, except where the acknowledgement has been made in the text. We have not submitted the project to any other institute for the requirement of any other degree.

Submitted by: - Date: 25 May 2022

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Certificate

This is to certify that the project report entitled "**Crypto Currency Price Predictor**" presented *by Dheeraj Maurya, Nikhil Chopra,* and *Shubhankar Saxena* in the partial fulfilment for the award of Bachelor of Technology in Computer Science and Engineering, is a record of work carried out by them under my supervision and guidance at the Department of Computer Science and Engineering at Institute of Engineering and Technology, Lucknow.

It is also certified that this project has not been submitted to any other Institute for the award of any other degrees to the best of my knowledge.

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Abstract

Because of its fundamental nature of integrating encryption technology with monetary units, Bitcoin has recently gotten a lot of interest in the disciplines of economics, cryptography, and computer science." By analysing the time series of the Bitcoin process, this experiment exposes the influence of Long Short Term Memory (LSTM). We also leverage the most important elements from Blockchain information that is deeply engaged in Bitcoin's supply and demand to train models to improve the forecasting performance of the most recent Bitcoin pricing process[2].

We have studied Cryptocurrencies like Bitcoin and Ethereum along with what exactly is cryptocurrency before jumping to its prediction. Along with that we have also tried to understand what is the underlying technology behind Cryptocurrency i.e Blockchain and how it works. We have developed a Web Application that predicts the price of Bitcoin and Ethereum using Long Short Term Memory (LSTM) in terms of Canadian Dollars.

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Project Objectives

- ❏ Introduce the concept of this project.
- ❏ Provide the reader with a rounded understanding of cryptocurrencies.
- ❏ Explain to the reader how volatile cryptocurrency prices can be.
- ❏ Describe in detail the applied aspect of this project.
- ❏ Create a simple web application which is easy to use and clear to understand.
- ❏ Deliver cryptocurrency prices to the user.
- ❏ Provide an educated guess as to future changes in prices.
- ❏ Work closely with the given learning outcomes for this project.
- ❏ Conduct work as a team.

Chapter 1

Introduction

1.1 What is Currency

Currency is a form of money which is used as a source of exchange, like coins. We can also say that currency is a type of money used over specific environments, especially under a nation. We can say U.S. Dollars, Indian rupee, Riyal as an example of currency which is legalised and used by different countries' governments. It can be used to trade between countries. Each currency has its own limitation for acceptance over countries.
We have almost 180 national currencies recognized by the UN to be used for circulation as of now. Other 66 countries used U.S. dollars for their trades.

1.2 What is Cryptocurrency

The term "cryptocurrency" refers to a digital currency that is encrypted and uses the cryptography process. Satoshi Nakamoto created the first cryptocurrency, Bitcoin, in 2008, and it has been in use since 2009. Since then, it has evolved into the most well-known cryptocurrency and the umbrella name for all cryptocurrencies and digital currencies. By the end of 2017, the market price of Bitcoin had risen to about 20,000 USD, and it now trades at around 8000 USD on average[3]. Technically, "mine" bitcoin implies that a very little amount of fees will be compensated in cryptocurrency by strengthening computational resources to participate in the cryptocurrency network and authorise transactions. Despite the fact that mining Bitcoin has become incredibly tough, its enormous potential and market worth have drawn more miners and developers to join this burgeoning business. Since its inception, the total quantity of Bitcoin has been increasing at an exponential rate. Cryptocurrency, unlike banknotes, is an encrypted digital money that cannot be printed[3].

1.3 Blockchain

The significant impact of cryptocurrency is inseparably linked with the blockchain technology, which is the key of Bitcoin and also the fundamental technique for other cryptocurrencies[3]. According to , blockchain adopted the distributed ledger technology and allowed the direct cryptocurrency transactions between buyer and seller to be saved digitally in a public-accessible distributed ledger permanently without any central authorization[3].

As a relatively new technology, blockchain is designed to achieve decentralisation, realtime peer-to-peer operation, anonymity, transparency, irreversibility and integrity in a widely applicable manner. However, there are still vulnerabilities and challenges related to this technology that should not be neglected[3].

1.4 Why Cryptocurrency

The goal of cryptocurrencies is to overcome the issues of traditional currencies by giving currency holders power and accountability. All cryptocurrencies adhere to money's five attributes and three functions. They each attempted to tackle one or more real-world issues as well. Cryptocurrency is a type of digital money that is more secure than traditional money [4].

Users and their digital funds are better safeguarded since transactions are public, immutable, basically tamper-proof, and governed by humans[4].

- Cryptocurrencies belong to everyone
- Cryptocurrencies are almost impossible to counterfeit
- Cryptocurrency transactions are (mostly) confidential
- Cryptocurrency security evolves with time and value [4]

1.5 Cryptocurrency Mining

There are 3 number one approaches to acquiring bitcoin and different cryptocurrencies. You should purchase them on a trade like Coinbase, obtain them as charge for items or services, or virtually “mine” them. It's the 1/3 class that we`re explaining here, the usage of Bitcoin as our example[5].

Crypto mining is the process of obtaining cryptocurrency by solving cryptographic equations with high-performance computers. It's a formula with a set of hard and fast properties that makes it particularly useful for encryption. The repairing system comprises confirming data blocks and adding transaction data to a public record (ledger), a blockchain that is safeguarded with the use of complex encryption algorithms. Cryptocurrencies employ a decentralised distribution method. Cryptographic algorithms are used to help with transaction verification. As a result, there may be no crucial authority or centralised ledger. To add new money to the ledger, you must solve sophisticated mathematical problems that aid in the verification and updating of digital foreign currency transactions on the decentralised blockchain record. The miners get paid in bitcoin as a consequence of their efforts. This is mining because it allows fresh money to enter the system [5].

- Specialised computers carry out the computations required to validate and record each new bitcoin transaction while also ensuring the blockchain's security. Blockchain verification necessitates a significant amount of processing power, which is given by volunteers.
- Bitcoin mining is comparable to running a large data centre. Companies purchase mining equipment and pay for the power that is required to operate (and cool) it. The value of the coins mined must be greater than the cost of mining those coins for this to be viable. What Drives Miners to Work? A lottery is held by the network operator. Each machine on the network competes to be the first to guess a "hash," a 64-digit

hexadecimal number. The miner is more likely to receive the reward if the computer can estimate quicker.[5]

- Winner receives a freshly minted number of bitcoins and updates the blockchain ledger with all newly validated transactions - thereby adding a new verified "block" comprising all such transactions to the chain. Predefined. (This happens every 10 minutes on average.) The payout is 6.25 bitcoins at the end of 2020, but it will be reduced in 2024 and every four years after that. In reality, as the difficulty of mining rises, the payout will fall until there are no more bitcoins to mine. There will be just 21 million bitcoins available. The last block should theoretically be mined in 2140. Miners will no longer rely on newly issued bitcoins as a reward, instead relying on the delivery fees they charge.[5]

Chapter 2
Literature Review

Machine learning (ML) is a sort of artificial intelligence that uses historical data to predict the future. Previous research has demonstrated that ML-based models not only produce an approximate or precise match with the actual outcome, but also improve the accuracy of the results. Neural networks (NNs), support vector machines (SVMs), and deep learning are examples of machine learning.[1]

The decision-making process must make the appropriate decisions at the appropriate times in order to reduce the risks connected with the investment process. Researchers used bitcoin returns collected over many minutes during a 3-hour period to aggregate RV data in the combined cryptocurrency prediction system based on LSTM. A number of machine learning approaches are employed to predict future values based on historical patterns, including ANN (MLP, GRU, and LSTM), SVM, and ridge regression, which are compared to a heterogeneously executed automated volatility model (HARV) with offset parameters. Researchers employ standard support vector machines and linear regression methods to forecast Bitcoin value. The findings reveal that the suggested system successfully predicts the price with high accuracy, indicating that the technology may be used to predict the prices of many other cryptocurrencies. This search takes into account a time series forecast that takes into account all dates. Bitcoin's closing price is used to create a Bitcoin prediction model[1].

Researchers solved both multiple regression strategies based on highly correlated variables and deep learning mechanisms employing conjugated gradients mixed with BTC price forecasts linear search using machine learning techniques. Bitcoin, Ethereum, and Ripple's price movements are studied. The researchers used powerful artificial intelligence frameworks such as fully-associated artificial neural networks (ANNs) and short-term recurrent neural networks (LSTMs), and discovered that ANNs focus on long-term history while LSTMs focus on short-term dynamics, implying that LSTMs are more efficient at extracting meaningful information from historical memory than ANNs[1].

The accuracy of logistic regression and linear discriminant analysis in predicting daily Bitcoin prices with high dimensional data was found to be 66 percent in a study on daily Bitcoin price prediction with high dimensional data. The employment of neural networks (NNs), support vector machines (SVMs), and random forests is investigated in this paper (RFs). The findings show that machine learning and sentiment analysis may be used to time cryptocurrency markets (only Twitter data can forecast individual coins) and that neural networks beat other models[1].

Through Yahoo Finance, the LSTM model is used to forecast and identify Bitcoin stock market prediction techniques that can anticipate a result of more than $12,600 within days of the prediction.

Researchers have concentrated on increasingly inventive models due to the significance of building a solid and trustworthy strategy for predicting bitcoin values. The association model forecasted using the linear and nonlinear components of the time series of the stock data set. CNN and Seq2Seq LSTM have been effectively coupled in nonlinear time series forecasting to develop dynamic models for short-term and long-term dependent models.

Using a multilinear regression model and evaluating two main cryptocurrencies in the capital markets, this study focuses on social aspects that are increasingly used for online transactions throughout the world. BTC and LTC are two types of cryptocurrency[1].
Researchers discovered that LTC has an R2 score of 44 percent and BTC has an R2 score of 59 percent. A conventional LSTM model and an LSTM with an AR model (2) were utilised in the reference. This study used the LSTM model to predict the daily Bitcoin price and developed a forecasting framework. To forecast BTC price, the study showed two types of prediction models created using Bayesian-optimised RNN and LSTM. According to research, LSTM outperforms other methods, with 52 percent accuracy and an RMSE of 8%[1].
The investment method is mostly based on the cryptocurrency's past pricing. The construction of a Markov chain is one of the most essential tactics on which investors rely. This technique comprises numerous decision trees that are used to predict which cryptocurrency delivers the highest return on investment and then compare that estimate to the real figure. This research focuses on LSTM models that can forecast the future price of cryptocurrencies using algorithms, due to the importance of prediction in the investing process, on which many people rely for revenue production. To aid investors, machine learning and artificial intelligence are being used to create reliable forecasting models[1].

Chapter 3

Methodology

This research focuses on LSTM models that can forecast future cryptocurrency values using machine learning algorithms and artificial intelligence methodologies, with the goal of assisting investors.

3.1 Processing the data

To achieve the aims of this project, we trained the model of cryptocurrency price prediction using historical cryptocurrency prices[1]. The model training is itself have five following stages-

(1) collecting historical cryptocurrency data;
(2) data preprocessing;
(3) data splitting;
(4) data exploration;
(5) model training;
(6) testing the models; and
(7) extracting and comparing the result

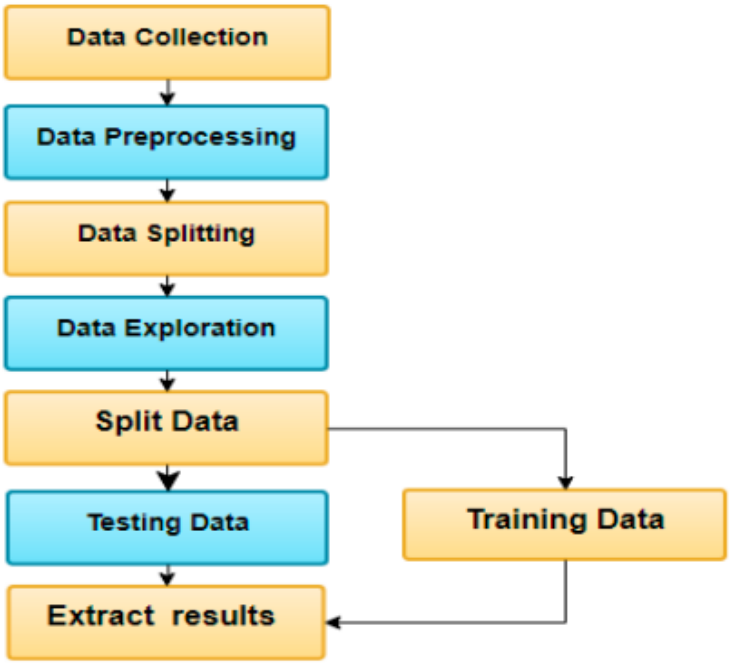

Figure 3.1.1. Methodology of processing data

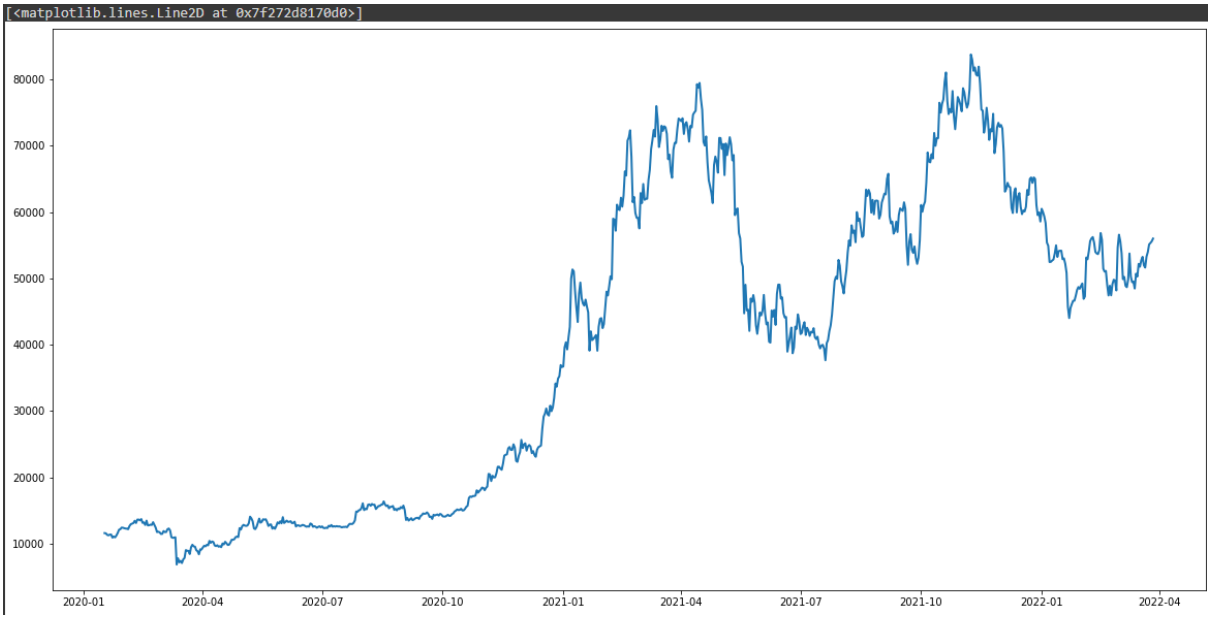

Fig 3.1.2. Training and testing dataset for BTC

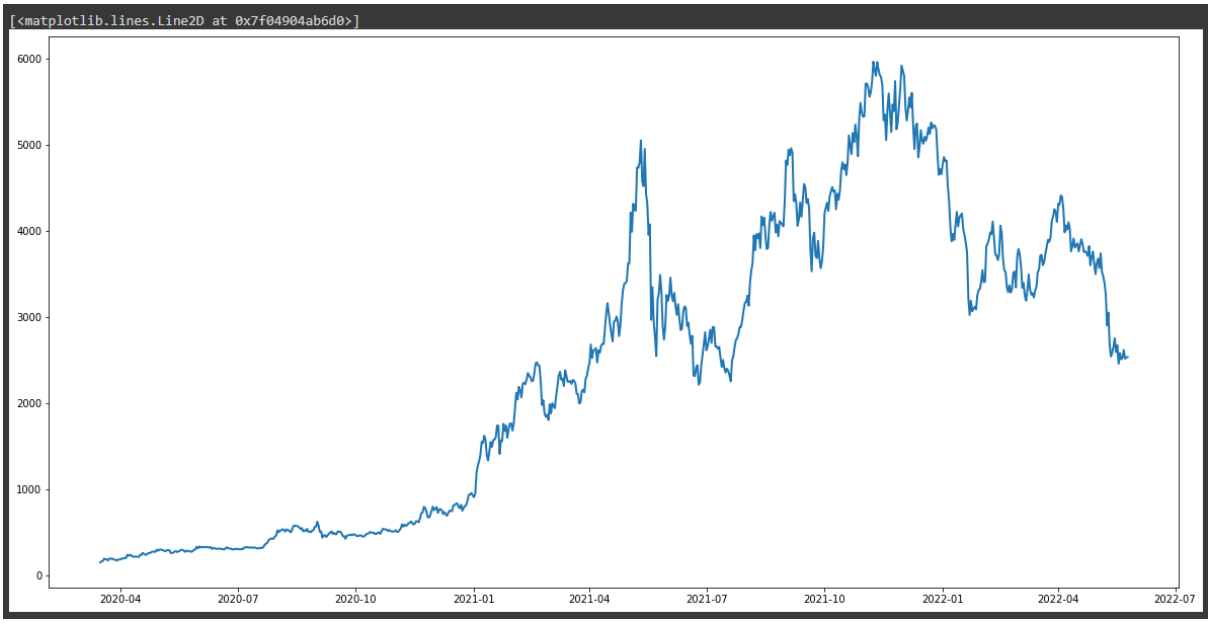

Fig 3.1.3 Training and testing dataset for ETH

3.2 Long Short Term Memory

Recurrent neural networks with long short-term memory (LSTM) have emerged as an effective and scalable technique for numerous learning problems using sequential input. Because they are general and effective, they are important for capturing long-term temporal relationships. The LSTM is an RNN-inspired design with gates that control information flow between cells. The input and forget gate structures can change information as it travels through the cell state, with the final output being a filtered version of the cell state dependent on the inputs' context. The LSTM design has been chastised for being haphazard and for including a large number of components whose function is unclear.As a result, it's questionable if the LSTM is the greatest design, and better ones are almost certainly available[1].

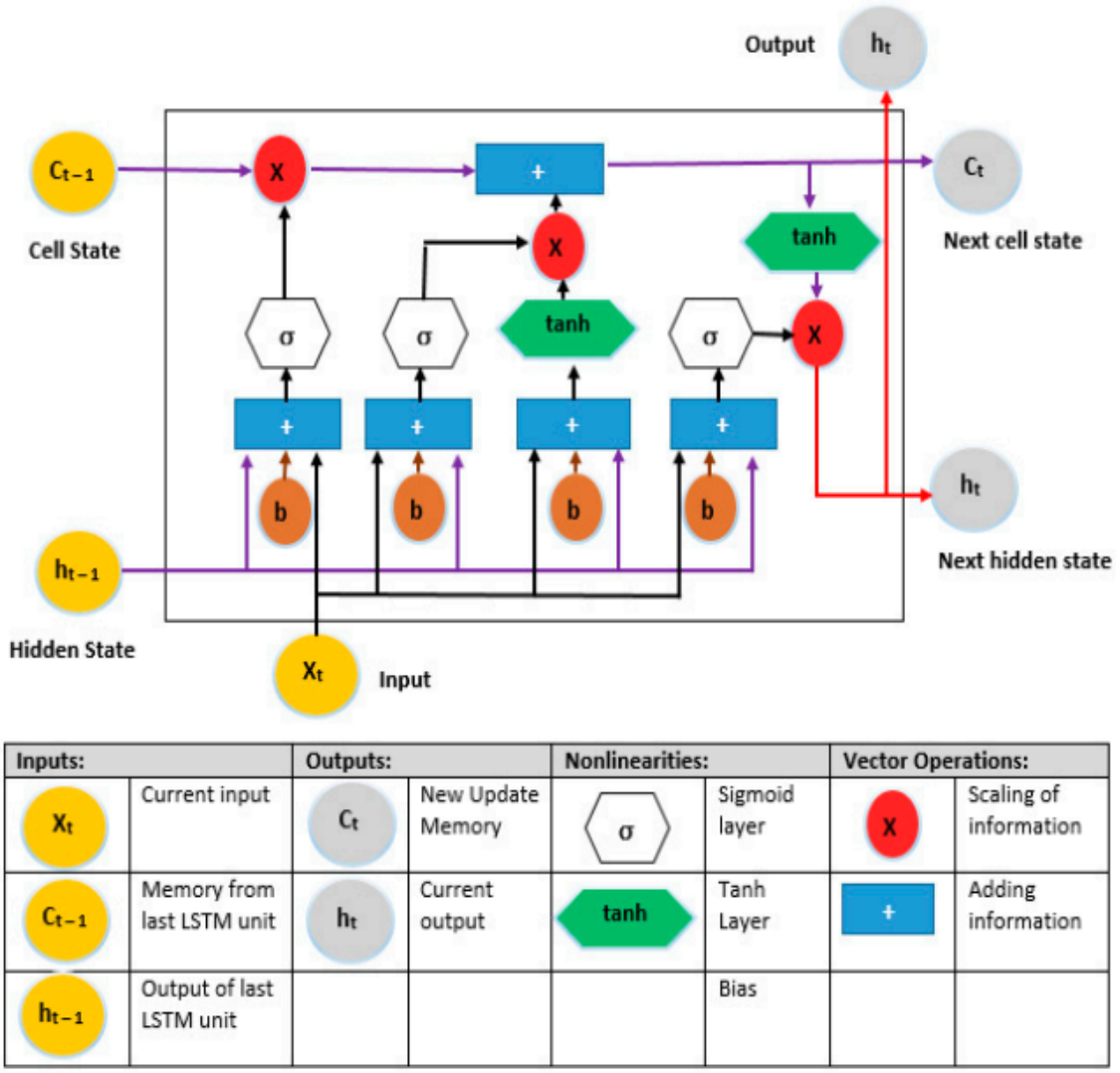

Fig 3.2.1. "The structure of a long short-term memory (LSTM) algorithm"

The forward training process of the LSTM can be formulated with the following equations:

$ft = \sigma\ Wf \cdot [ht-1, xt] + bf$ (forget factor) (1)

$it = \sigma\ Wf \cdot [ht-1, xt] + bi$ (ignore factor)(2)

$Ct = ft * Ct-1 + it * \tanh(Wc \cdot [ht-1, xt] + bc)$ (Cell memory) (3)

$Ot = \sigma(W0 \cdot [ht-1, xt] + b0)$ (4)

$ht = ot * tabh(Ct)$ (5)

where it, ot and ft represent the activation of the input port, output port, and forget port, respectively; Ct and ht specify the activation vector for each cell and memory block, respectively; and W and b represent the weight matrix and bias vector, respectively. Furthermore, σ(◦) denotes the sigmoid function [1].

3.3 Dataset

The analysed dataset is collected from the open public api by cryptocompare.com. The api link is as - https://min-api.cryptocompare.com/data/histoday?fsym=BTC&tsym=CAD&limit=800

Where 'fsym=BTC' means the api will give the dataset for Bitcoin, 'tsym=CAD' tells that the price of bitcoin is in the form of Canadian Dollars and 'limit=800' means that we are asking for the data of last 800 day.

- The dataset was divided into 70%-30% for training and testing purpose.
- We have taken CAD (Canadian Dollars) into consideration as it fluctuates less than Indian Rupees. INR have a lower performance because of the inflation these days.

Variable Name	Variable Description	Data Type
Date	Date of Observation	Date
Open	Opening price on the given day	Number
High	High price on the given day	Number
Low	Low price on the given day	Number
Close	Close price on the given day	Number

Fig 3.3 Dataset Specification

time	high	low	open	close	time
2020-03-16	7397.40	6000.00	7392.10	7056.40	2020-03-16
2020-03-17	7858.70	6944.60	7056.40	7607.00	2020-03-17
2020-03-18	7883.40	7207.00	7607.00	7825.00	2020-03-18
2020-03-19	9355.90	7724.40	7825.00	9012.40	2020-03-19
2020-03-20	9859.40	8200.00	9012.40	8910.70	2020-03-20
...	...	...	...	...	...
2022-05-21	37984.58	37173.15	37420.66	37703.88	2022-05-21
2022-05-22	38995.69	37481.88	37703.88	38856.05	2022-05-22
2022-05-23	39138.84	36918.26	38856.05	37161.03	2022-05-23
2022-05-24	38171.58	36642.62	37161.03	37995.98	2022-05-24
2022-05-25	38663.05	37762.72	37995.98	38131.32	2022-05-25

801 rows × 5 columns

Table 3.3.1 Sample of data from BTC dataset

time	high	low	open	close	time
2020-03-16	164.41	153.83	170.61	155.73	2020-03-16
2020-03-17	171.31	164.08	155.73	165.60	2020-03-17
2020-03-18	172.46	169.10	165.60	171.45	2020-03-18
2020-03-19	202.06	193.68	171.45	199.35	2020-03-19
2020-03-20	202.27	183.03	199.35	191.40	2020-03-20
...	...	...	...	...	...
2022-05-21	2544.63	2520.50	2511.67	2529.18	2022-05-21
2022-05-22	2626.67	2603.36	2529.18	2620.45	2022-05-22
2022-05-23	2538.47	2497.59	2620.45	2519.15	2022-05-23
2022-05-24	2583.35	2523.69	2519.15	2535.09	2022-05-24
2022-05-25	2591.20	2488.94	2535.09	2531.16	2022-05-25

801 rows × 5 columns

Table 3.3.2 Sample of data from ETH dataset

3.4 Machine model factors

These are the factors which effects the everyday prices of cryptocurrency and these factors can be the potential variables for machine learning models. Some of the factors have long tern influence while some have short term influence.

3.4.1 Famous personalities influence -

This have the short term influence on the people resulting in steep rise or fall of the cryptocurrency. So this does not propose any major hindrance to our current model. Our model will be able to cope up with the influence on the next restart of the server ie. on the next day, if we are restarting the server everyday.

3.4.2 Government legalization or spreading awareness on mass scale -

This have the long term influence on the people resulting in steep rise or fall of the cryptocurrency. As our model is trained in such a way, it has already taken a lot of historical data for building the model. The historical data contains the prices of certain cryptocurrency for the past 800 days. The model already have the data which has seen the legalization of cryptocurrency in many countries. Our model will be able to cope up with the influence on the next restart of the server ie. on the next day, if we are restarting the server everyday.

3.4.3 Cost of mining

This have the perpetual effect on the cryptocurrency, and the effect is not huge enough to drastically change the price of cryptocurrency.

3.4.4 Market capital

We have taken this into consideration assuming it has the major effect on the cryptocurrency value. The public api which is giving us the crypto coin data have the fields as given in figure 5. As we have the aim to predict the future price for the next 30 days, so the model needs to predict every field for the time series data frame. It will potentially reduce the performance score of the independent variable which has to be predicted for the next 30 days. In order to predict the future price effectively, an assumption is to be made which results in dropping the entire dependent fields except closing price of the crypto coins. As we have to predict the future price the everyday closing price for crypto coin is taken into consideration.

Taking closing price into consideration and building the time frame machine learning model gives an extremely efficient model which have the mean absolute percentage error range of 4.4% to 8%.

3.5 Backend and Database Choices

We have prior experience in NodeJs for building the backend. But to avoid the cross platform communication we have to consider the frameworks which is built onto the same language as Python3. So, as per our research two frameworks, flask and django are in market trends. But django have the ability to work on multithreading, this potential of django can be helpful for future expansion of the project, when we add more coins to the project then multithreading can be helpful to decrease the model training time.

Django have the built-in support for SQLite and prior working experience helps us to work on it.

Simple HTML CSS and Javascript is used along with AJAX call at the front end.

3.6 Limitations

3.6.1 We haven’t covered many points like famous personalities' influence over the coin, government legalisation and awareness.

3.6.2 The model is built solely on the assumption that only building the model on closing prices will give the best results.

3.6.3 Our app is dependent on the external api which provides us the dataset of cryptocurrencies. If the api goes down it would affect our application.

3.6.4 As we are using the external api service, there is a limit of using the api.

3.6.5 Currently our application is single threaded, so it is not feasible enough to use for multiple different data sets. If multiple different dataset is used to build multiple models for prediction, it will result in consumption of a lot of time.

Chapter 4

Result

After running the application, we are able to get the following results. The graph also shows the comparison between the actual and the predicted data. We are able to get the prediction score close to **88%.**

Best mean absolute percentage error = 4.42%

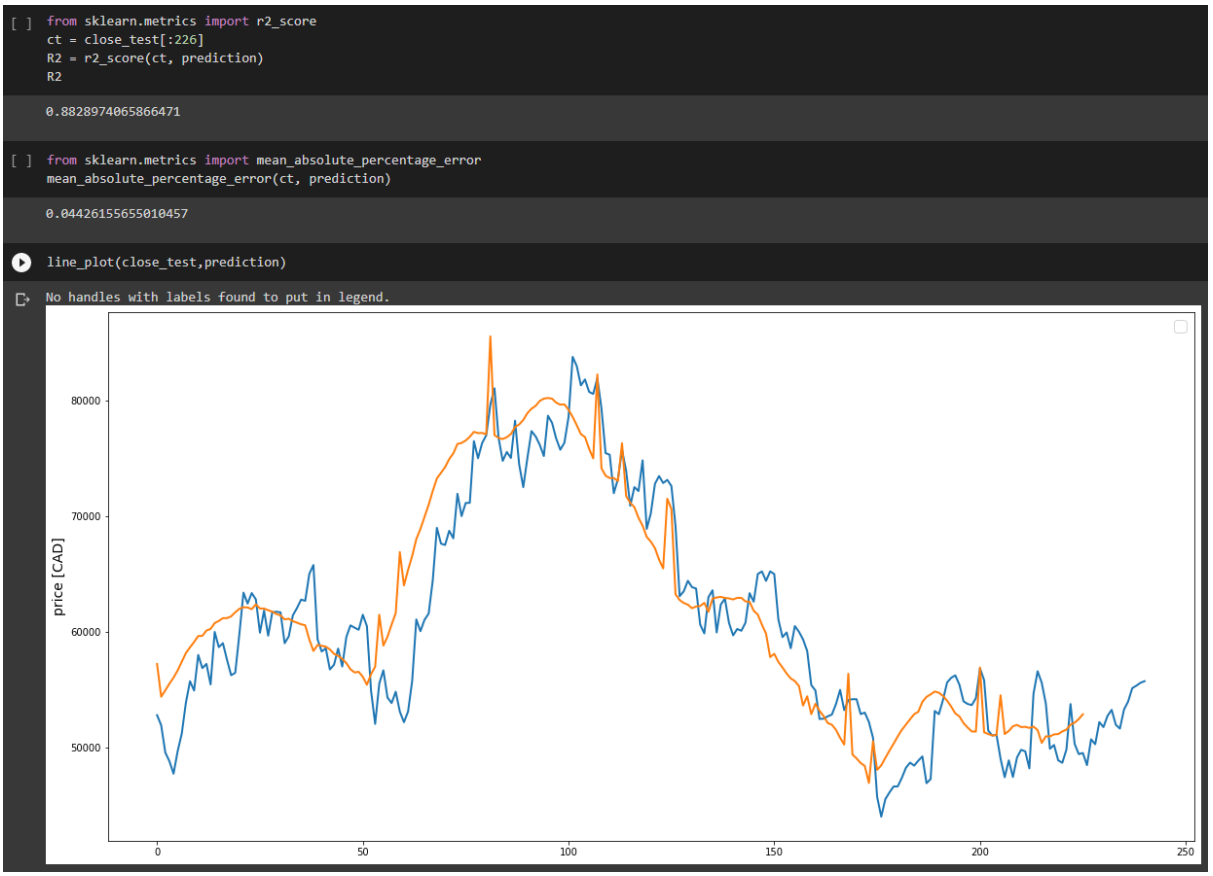

Fig 4.1 Performance score and testing and training graph

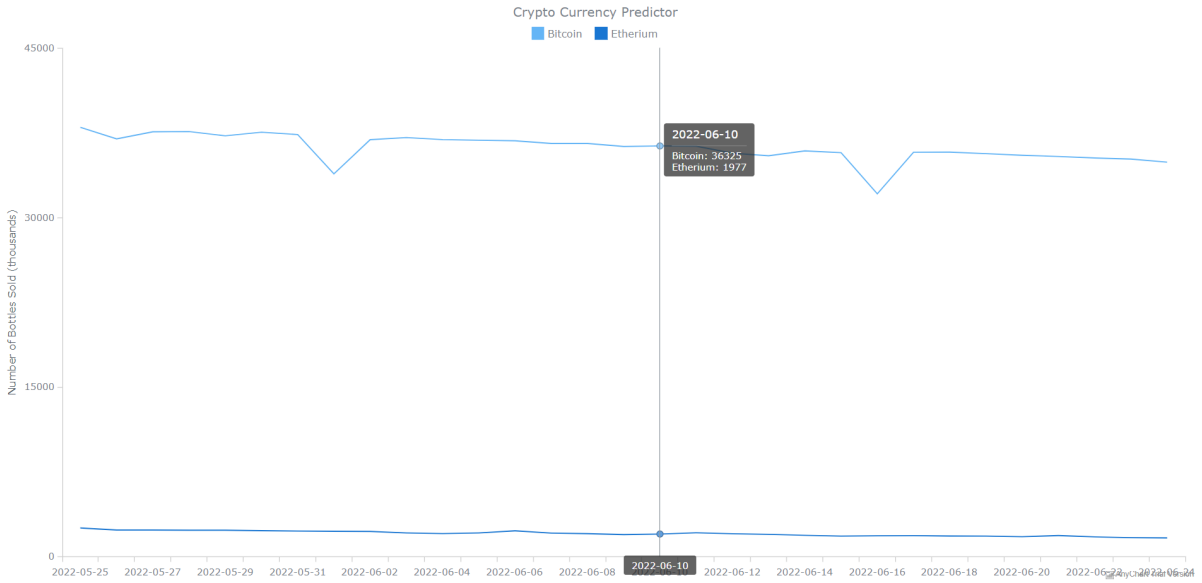

Fig 4.2 Prediction graph for ETH and BTC combined

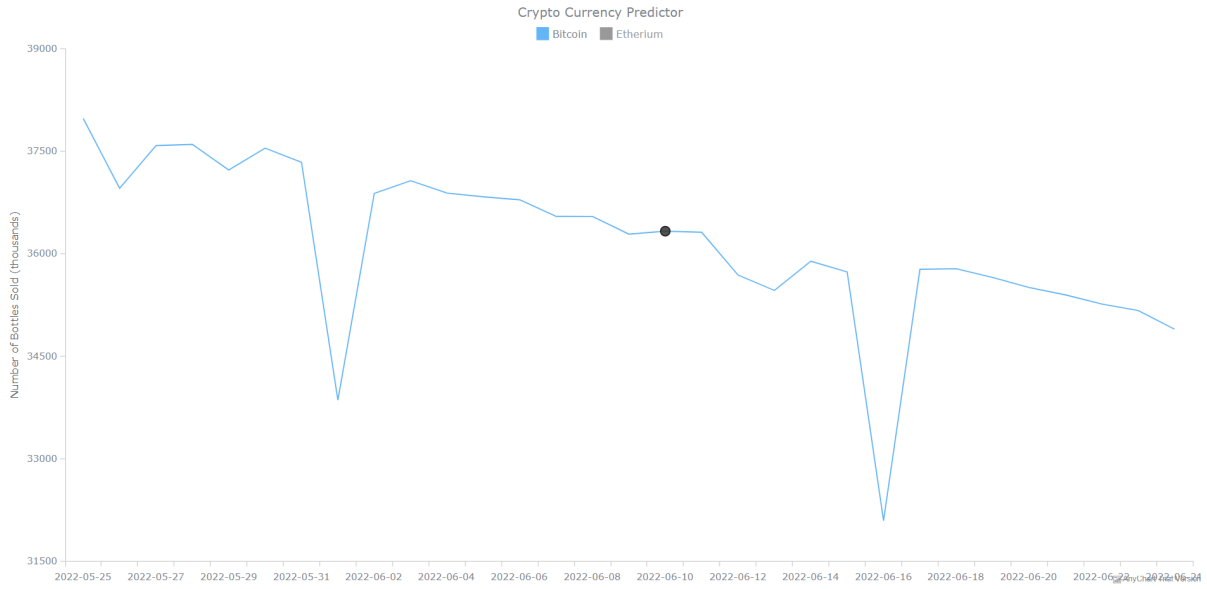

Fig 4.3 Prediction graph for BTC

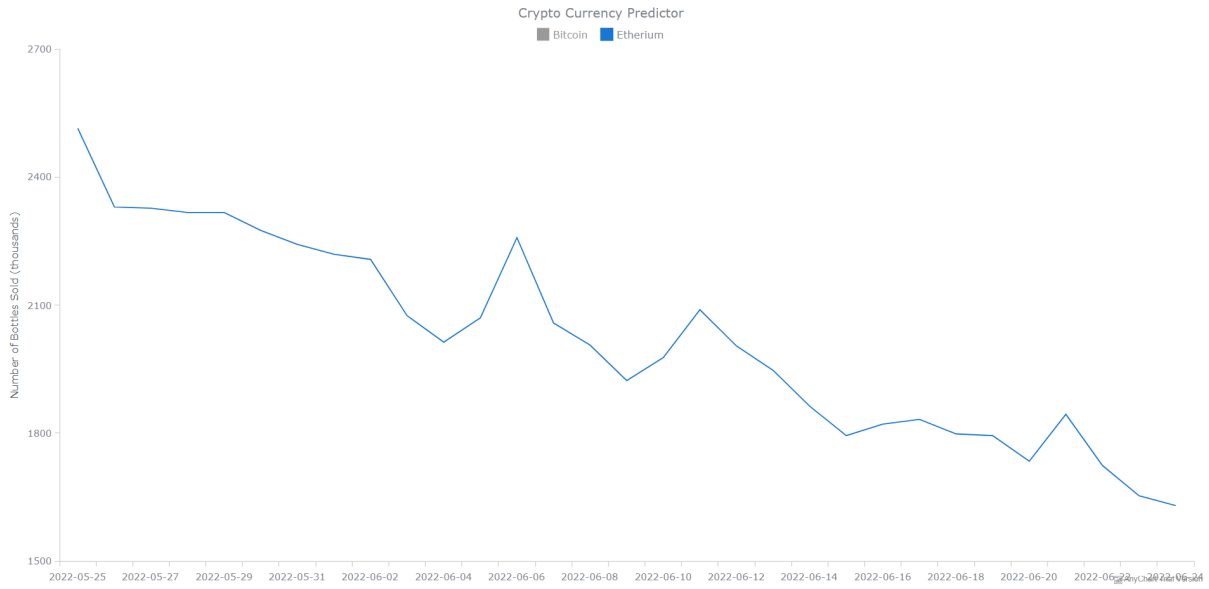

Fig 4.4 Prediction graph for ETH

	time	close
0	2022-05-25	2514.640000
1	2022-05-26	2330.124023
2	2022-05-27	2327.101074
3	2022-05-28	2317.402832
4	2022-05-29	2317.280762
5	2022-05-30	2275.197021
6	2022-05-31	2242.864014
7	2022-06-01	2219.233887
8	2022-06-02	2207.069092
9	2022-06-03	2075.768799
10	2022-06-04	2013.141724
11	2022-06-05	2070.286865
12	2022-06-06	2258.070312
13	2022-06-07	2058.389404
14	2022-06-08	2006.044434
15	2022-06-09	1923.990479
16	2022-06-10	1977.758423
17	2022-06-11	2089.101562
18	2022-06-12	2004.339722
19	2022-06-13	1947.851929
20	2022-06-14	1863.587036
21	2022-06-15	1794.637329
22	2022-06-16	1821.982666
23	2022-06-17	1832.703613
24	2022-06-18	1798.744629
25	2022-06-19	1794.805420
26	2022-06-20	1734.276733
27	2022-06-21	1844.259155
28	2022-06-22	1724.497192
29	2022-06-23	1653.968994
30	2022-06-24	1630.745850

Table 4.1 Machine model output in console

Chapter 5

Conclusion

With the growing popularity of cryptocurrencies, it's become critical to design a system that can reliably and effectively anticipate their price. The goal of the research was to discover the most effective method for predicting bitcoin prices. All investors and traders can utilise the research as a basic tool. It would assist consumers in carrying out their investments in a more effective manner.

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[6] https://developer.mozilla.org/en-US/docs/Learn/Server-side/Django/skeleton_website

[7] https://www.geeksforgeeks.org/how-to-create-an-app-in-django/

Code Snippet

Machine model code

“Import the necessary files in mlmodel file”

```
“import json”
“import requests”
“from keras.models import Sequential”
“from keras.layers import Activation, Dense, Dropout, LSTM”
“import matplotlib.pyplot as plt”
“import numpy as np”
“import pandas as pd”
“import seaborn as sns”
“from sklearn.metrics import mean_absolute_error”
“from keras.preprocessing.sequence import TimeseriesGenerator”
“# %matplotlib inline”
“from GetDataAPI.models import CryptoPrice”
“from datetime import datetime”
```

./base/mlmodel

```
class CryptoModel:
    def __init__(self,coin_passed):
        self.coin = coin_passed
        self.flagg = 0
        print(self.coin)
        if self.coin == 'ETH':
            self.flagg = 2
        else:
            self.flagg = 1

    def runmodel(self):
         endpoint = 'https://min-api.cryptocompare.com/data/histoday'
        res = requests.get(endpoint + '?fsym=' +  self.coin + '&tsym=CAD&limit=800')
        hist = pd.DataFrame(json.loads(res.content)['Data'])
        hist = hist.set_index('time')
        hist.index = pd.to_datetime(hist.index, unit='s')
        hist['time'] = pd.to_datetime(hist.index, unit='s')
        target_col = 'close'

        hist.drop(["conversionType",
"conversionSymbol","high","low","open","volumefrom","volumeto"  ], axis = 'columns',
inplace = True)

        close_data = hist['close'].values
        close_data = close_data.reshape((-1,1))
```

```
split_percent = 0.70
split = int(split_percent*len(close_data))

close_train = close_data[:split]
close_test = close_data[split:]

date_train = hist['time'][:split]
date_test = hist['time'][split:]

look_back = 15

 train_generator = TimeseriesGenerator(close_train, close_train,
                                       length=look_back,
                                       batch_size=20)
test_generator = TimeseriesGenerator(close_test,
                                     close_test,
                                     length=look_back,
                                     batch_size=1)

model = Sequential()
model.add(LSTM(100,activation='relu',input_shape=(look_back,1)))
model.add(Dense(1))
model.add(Dropout(.02))
model.compile(optimizer='adam', loss='mse')

num_epochs = 15
model.fit(train_generator, epochs=num_epochs, verbose=1)

prediction = model.predict(test_generator)

close_train = close_train.reshape((-1))
close_test = close_test.reshape((-1))
prediction = prediction.reshape((-1))
ct = close_test[:226]

# from sklearn.metrics import mean_absolute_percentage_error
# mean_absolute_percentage_error(ct, prediction)
from sklearn.metrics import r2_score
ct = close_test[:226]
R2 = r2_score(ct, prediction)
R2
close_data = close_data.reshape((-1))

num_prediction = 30

prediction_list = close_data[-look_back:]
for _ in range(num_prediction):
    x = prediction_list[-look_back:]
    x = x.reshape((1, look_back, 1))
    out = model.predict(x)[0][0]
```

```
            prediction_list = np.append(prediction_list, out)
        prediction_list = prediction_list[look_back-1:]
        forecast = prediction_list


        last_date = hist['time'].values[-1]
        prediction_dates = pd.date_range(last_date, periods=num_prediction+1).tolist()
        forecast_dates = prediction_dates

        print(forecast)

        forecast_dates

        df = pd.DataFrame({'time' : forecast_dates,'close':forecast})
        print(df)
        arr = df.to_numpy()
        for i in arr:
            k = str(i[0])
            k = k[:10]
            # print(k,i[1])
            cyptoObject = CryptoPrice.objects.create(date=datetime.strptime(k,
'%Y-%m-%d'),value=i[1],flag=self.flagg)
            cyptoObject.save()
        # return df
```

Front-End

./base/template/index.html

```
<html>
<head>
  <script src="https://cdn.anychart.com/releases/v8/js/anychart-base.min.js"></script>
  <script src="https://cdn.anychart.com/releases/v8/js/anychart-ui.min.js"></script>
  <script src="https://cdn.anychart.com/releases/v8/js/anychart-exports.min.js"></script>
  <link href="https://cdn.anychart.com/releases/v8/css/anychart-ui.min.css" type="text/css"
rel="stylesheet">
  <link href="https://cdn.anychart.com/releases/v8/fonts/css/anychart-font.min.css"
type="text/css" rel="stylesheet">
  <style type="text/css">

    html,
    body,
    #container {
      width: 100%;
      height: 100%;
```

```
      margin: 0;
      padding: 0;
    }

</style>
</head>
<body onload ="mount();">

  <div id="container"></div>

  <script>

    var dataArray = new Array(31);
    // var dataSet;
    function mount(){
       let fetchRes = fetch("http://localhost:8000/testAPI/");
       fetchRes
          .then(res => res.json())
          .then(d => {
             for(let i=0; i<31; i++){
               dataArray[i] = new Array(3);
               // dataArray.push([d[i].date.slice(0,10), d[i].value, d[i+31].value ]);
               dataArray[i][0] = d[i].date.slice(0,10) , dataArray[i][1] = d[i].value ,
dataArray[i][2] = d[i +  31].value

             // dataSet = anychart.data.set(
             //   dataArray
             // );
            }
       crypto();
       console.log("in")
       })
       console.log("out")
    }

    // anychart.onDocumentReady(
    function crypto() {
      console.log("  outer ")

      var dataSet = anychart.data.set(
        dataArray
      );

      var btcData = dataSet.mapAs({ x: 0, value: 1 });

      var etherData = dataSet.mapAs({ x: 0, value: 2 });

      // create line chart
      var chart = anychart.line();
```

```
    // turn on chart animation
    chart.animation(true);

    // set chart padding
    chart.padding([10, 20, 5, 20]);

    // turn on the crosshair
    chart.crosshair().enabled(true).yLabel(false).yStroke(null);

    // set tooltip mode to point
    chart.tooltip().positionMode('point');

    // set chart title text settings
    chart.title(
      ' Crypto Currency Predictor  '
    );


    chart.xAxis().labels().padding(5);

    var btc = chart.line(btcData);
    btc.name('Bitcoin');
    btc.hovered().markers().enabled(true).type('circle').size(4);
    bt..tooltip().position('right').anchor('left-center).offsetX(5).offsetY(5);

    var ether = chart.line(etherData);
    ether.name('Etherium');
    ether.hovered().markers().enabled(true).type('circle').size(4);
    ether.tooltip().position('right').anchor('left-center').offsetX(5).offsetY(5);


    chart.legend().enabled(true).fontSize(13).padding([0, 0, 10, 0]);
    chart.container('container');
    chart.draw();
  };

</script>
</body>
</html>
```

Back-End

Replace “INSTALLED_APPS in settings.py”
./base/cryptoPredictionProject/settings.py

```
"""
Django settings for cryptoPredictorProject project.

Generated by 'django-admin startproject' using Django 3.2.13.

For more information on this file, see
https://docs.djangoproject.com/en/3.2/topics/settings/

For the full list of settings and their values, see
https://docs.djangoproject.com/en/3.2/ref/settings/
"""

# Application definition

INSTALLED_APPS = [
    'django.contrib.admin',
    'django.contrib.auth',
    'django.contrib.contenttypes',
    'django.contrib.sessions',
    'django.contrib.messages',
    'django.contrib.staticfiles',
    'rest_framework',
    'GetDataAPI'
]
```

./base/cryptoPredictionProject/urls.py

```
from django.urls import path
from GetDataAPI import views
from mlmodel import CryptoModel
from GetDataAPI.models import CryptoPrice

def scriptt():
    CryptoPrice.objects.all().delete()
    CryptoModel('BTC').runmodel()
    CryptoModel('ETH').runmodel()
    # print(111111)

urlpatterns = [
```

```
    path('admin/', admin.site.urls),
    path('test/', views.index, name='test'),
    path('test1/', views.index1, name='test1'),
    path('testAPI/', views.CryptoPriceViewSet, name='testAPI')
]

scriptt()
```

./base/GetDataApi/models.py

```
from django.db import models

class CryptoPrice(models.Model):
            date = models.DateTimeField()
            value = models.BigIntegerField()
            flag = models.IntegerField()
```

./base/GetDataApi/serializer.py

```
from rest_framework import serializers
from GetDataAPI.models import CryptoPrice

class CryptoPriceSerializer(serializers.ModelSerializer):
   class Meta:
      model = CryptoPrice
      fields = ('date', 'value', 'flag')
```

./base/GetDataApi/views.py

```
from django.shortcuts import render
from django.http import HttpResponse
from rest_framework import viewsets
from rest_framework.response import Response
from rest_framework.decorators import api_view

from GetDataAPI.serializers import CryptoPriceSerializer
from GetDataAPI.models import CryptoPrice


@api_view(['GET'])
def CryptoPriceViewSet(request):
```

```
    queryset = CryptoPrice.objects.all()
    serializer_class = CryptoPriceSerializer(queryset,many="True")
      # HttpResponse("Hello, world. You're at the polls testapi.")
    return Response(serializer_class.data)

def index(request):
    return render(request, 'index.html', {"college":"iet"})


def index1(request):
    return HttpResponse("Hello, world. You're at the polls index1.")
```