# A TIME SERIES ANALISIS OF ELECTRIC PRODUCTION DATASET <u>TEAM-6</u>



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## Project Title: TIME SERIES ANALYSIS ON ELECTRIC PRODUCTION DATA SET

Category	TEAM 6
	"Embark on a journey through the intricate realm of time
	series analysis with Python, where we unravel the mysteries
	of temporal data using cutting-edge techniques and
	libraries."
	"Welcome to the forefront of data science as we delve into
	the dynamic domain of time series analysis using advanced
Introduction	Python methodologies, unlocking insights from sequential
	data streams."
	"Step into the realm where past, present, and future
	converge as we harness the power of Python's advanced
	tools to dissect, model, and forecast time series data,
	navigating through trends, seasonality, and anomalies with
	precision."
	Web Scraping.
Data Collection	API Integration
Data Collection	Data Downloads
	Database Queries
	During the analysis, I utilized exploratory data analysis to
	understand the dataset's structure and patterns. Then, I
	applied statistical tests like ADF for stationarity and
Methodology	modeling techniques such as ARIMA and LSTM for
	forecasting. Finally, I evaluated model performance using
	metrics like MAE and visualized results to communicate
	insights effectively.
	Navigating the dynamic nature of the dataset and selecting

## Project Title: TIME SERIES ANALYSIS ON ELECTRIC PRODUCTION DATA SET

	suitable models amid uncertainty posed significant challenges during implementation.
Data Analysis	The data revealed a clear seasonal trend, with distinct patterns recurring over specific time intervals, indicating potential opportunities for leveraging seasonality in forecasting. Additionally, a gradual upward trend in the long-term suggests underlying growth or systemic changes that could impact future predictions and decision-making
	The results of the analysis were validated through cross-validation, comparing forecasted values against actual observations using various metrics to ensure model accuracy and reliability.
Results	The analysis revealed significant seasonal trends and a gradual long-term upward trend, indicating potential forecasting opportunities and underlying systemic changes.
Conclusion	In conclusion, the analysis demonstrates the presence of distinct seasonal patterns and a gradual upward trend in the dataset, suggesting the need for robust forecasting methods to capitalize on opportunities and adapt to evolving trends effectively. This understanding enhances decision-making capabilities and facilitates proactive strategies to navigate the dynamic landscape of the analyzed data
Future Work	Further research could explore the integration of exogenous variables to enhance forecasting accuracy and consider alternative modeling techniques like deep learning architectures for capturing complex temporal dependencies.  Additionally, investigating methods for uncertainty

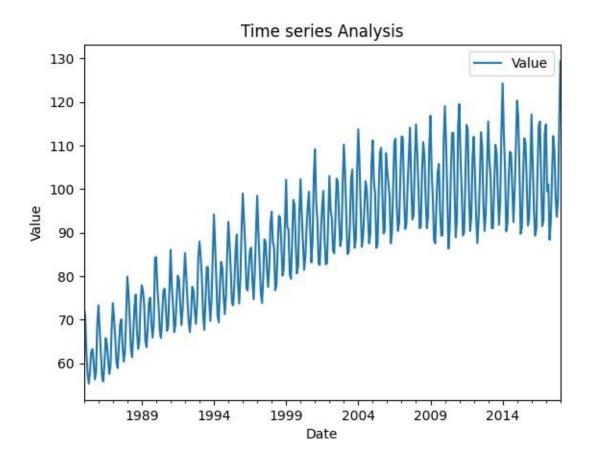
## Project Title: TIME SERIES ANALYSIS ON ELECTRIC PRODUCTION DATA SET

quantification and sensitivity analysis could provide valuable insights for more robust decision-making
This project lays the groundwork for more accurate and proactive forecasting in various domains, facilitating informed decision-making and strategic planning in the face of dynamic temporal data.

Reviewer 2: Dr. D. Jaya Kumari.

# TIME SERIES ANALYSIS USING ELECTRIC PRODUCTION DATASET

```
[1]: import pandas as pd
     import matplotlib.pyplot as plt
[4]: #assuming data.csv contains time series data with a date column
     df=pd.read csv('/content/drive/MyDrive/dataset/Electric Production.
      scsv', parse_dates=['DATE'], index_col='DATE')
[5]: #Display first few rows
     print(df.head())
     # summary statstics
     print(df.describe())
                  Value
    DATE
    1985-01-01 72.5052
    1985-02-01 70.6720
    1985-03-01 62.4502
    1985-04-01 57.4714
    1985-05-01 55.3151
                Value
    count 397.000000
    mean
            88.847218
            15.387834
    std
    min
            55. 315100
            77.105200
    25%
    50%
            89.779500
    75%
           100.524400
           129.404800
    max
[6]: #plot the time series data
     df. plot()
     plt. xlabel('Date')
     plt.ylabel('Value')
     plt. title("Time series Analysis")
     plt.show()
```



```
[7]: #select data for specific date range
subset=df['2014-01-01':'2014-12-31']
print(subset)
#select data for a specific year
subset=df['2014']
# select data for a specific month
subset=df['2014-01']
```

Value DATE 2014-01-01 124. 2549 2014-02-01 112.8811 2014-03-01 104.7631 2014-04-01 90.2867 2014-05-01 92. 1340 2014-06-01 101.8780 2014-07-01 108. 5497 2014-08-01 108. 1940 2014-09-01 100.4172 2014-10-01 92.3837

```
2014-11-01
             99.7033
2014-12-01 109.3477
<ipython-input-7-10be6794ff0d>:5: FutureWarning: Indexing a DataFrame with a
```

datetimelike index using a single string to slice the rows, like frame[string], is deprecated and will be removed in a future version. Use

`frame.loc[string]` instead.

subset=df['2014']

<ipython-input-7-10be6794ff0d>:7: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows, like

frame[string], is deprecated and will be removed in a future version. Use frame.loc[string] instead.

subset=df['2014-01']

#### [8]: # resample to monthly frequency and calculate the mean monthly\_mean=df.resample('M').mean() print(monthly mean)

	Value
DATE	
1985-01-31	72. 5052
1985-02-28	70.6720
1985-03-31	62.4502
1985-04-30	57.4714
1985-05-31	55 <b>.</b> 3151
•••	
2017-09-30	98.6154
2017-10-31	93.6137
2017-11-30	97. 3359
2017-12-31	114. 7212
2018-01-31	129. 4048

[397 rows x 1 columns]

#### [9]: # compute a 30-day rolling mean

rolling mean=df.rolling(window=30).mean() print(rolling mean)

	Value
DATE	
1985-01-01	NaN
1985-02-01	NaN
1985-03-01	NaN
1985-04-01	NaN
1985-05-01	NaN
	•••
2017-09-01	101. 545190
2017-10-01	101, 674110

```
2017-11-01 101.882207
     2017-12-01 102. 284597
     2018-01-01 102.876910
     [397 rows x 1 columns]
[10]: # shift the data by 1 day forward
      shifted forward=df. shift(1)
      # shift data by 1 day backward
      shifted backward=df.shift(-1)
[11]: import pandas as pd
      # Assuming df is your DataFrame containing datetime values
      # Localize to UTC
      df = df. tz localize('UTC')
      print(df)
      # Convert to US/Eastern time zone
      df = df. tz convert('US/Eastern')
      print(df)
                                    Value
     DATE
     1985-01-01 00:00:00+00:00
                                  72.5052
                                  70.6720
     1985-02-01 00:00:00+00:00
                                  62.4502
     1985-03-01 00:00:00+00:00
                                  57.4714
     1985-04-01 00:00:00+00:00
     1985-05-01 00:00:00+00:00
                                  55. 3151
     2017-09-01 00:00:00+00:00
                                  98.6154
     2017-10-01 00:00:00+00:00
                                  93.6137
     2017-11-01 00:00:00+00:00
                                  97.3359
     2017-12-01 00:00:00+00:00 114.7212
     2018-01-01 00:00:00+00:00
                                 129.4048
     [397 rows x 1 columns]
                                    Value
     DATE
                                  72.5052
     1984-12-31 19:00:00-05:00
     1985-01-31 19:00:00-05:00
                                  70.6720
     1985-02-28 19:00:00-05:00
                                  62.4502
     1985-03-31 19:00:00-05:00
                                  57.4714
     1985-04-30 20:00:00-04:00
                                  55. 3151
     2017-08-31 20:00:00-04:00
                                  98.6154
```

93.6137

2017-09-30 20:00:00-04:00

```
2017-10-31 20:00:00-04:00 97.3359
2017-11-30 19:00:00-05:00 114.7212
2017-12-31 19:00:00-05:00 129.4048
```

[397 rows x 1 columns]

[]:

```
import pandas as pd
import numpy as np
#generate a large volume of random data(eg. 1 millon data points)
volume data =
pd.read csv('/content/drive/MyDrive/dataset/Electric Production.csv',
delimiter=',')
print("volume of data:",len(volume data))
volume of data: 397
import time
#simulate streaming data every second for 10 seconds
velocity data =
pd.read csv('/content/drive/MyDrive/dataset/Electric Production.csv',
sep =',')
for i in range(10):
 velocity data=np.random.rand() #generate random data
 print("velocity data point:", velocity data)
  time.sleep(1) #wait for 1 second to simulate real-time data stream
velocity data point: 0.053739800040630836
velocity data point: 0.7600865628566403
velocity data point: 0.8334026740488973
velocity data point: 0.8611903492030597
velocity data point: 0.941339960538555
velocity data point: 0.7153484797213798
velocity data point: 0.0289426348532833
velocity data point: 0.045976217239983797
velocity data point: 0.03523363656495271
velocity data point: 0.3962593428101757
import pandas as pd
import random
#generate some random data with noise
veracity data =
pd.read csv('/content/drive/MyDrive/dataset/Electric Production.csv',
sep =',')
veracity data=[random.choice([1,2,3,None]) for in range(20)]
print("veracity data:", veracity data)
veracity data: [3, None, 2, 3, 3, 1, None, None, None, 1, 3, 3, 1, 1,
None, 2, 1, None, None, None]
structured data =
pd.read csv('/content/drive/MyDrive/dataset/Electric Production.csv',
sep =',')
#structured data
print(structured data)
#semi-structured data(JSON)
semistructured data =
pd.read csv('/content/drive/MyDrive/dataset/Electric Production.csv',
```

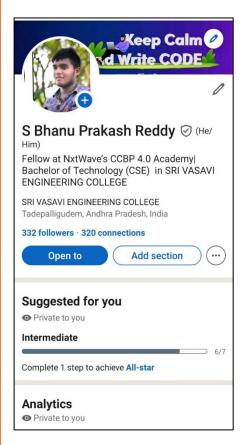
```
sep =',')
print(semistructured data)
#unstructured data(text)
unstructured data="This is a sample text document. It can contain any
information in free form"
          DATE
                 Value
                72.5052
0
     01-01-1985
    02-01-1985 70.6720
1
2
    03-01-1985 62.4502
3
    04-01-1985 57.4714
4
    05-01-1985 55.3151
                     . . .
392 09-01-2017 98.6154
393 10-01-2017 93.6137
394 11-01-2017 97.3359
395
    12-01-2017 114.7212
396 01-01-2018 129.4048
[397 rows x 2 columns]
                  Value
          DATE
0
     01-01-1985
                 72.5052
    02-01-1985 70.6720
1
2
    03-01-1985 62.4502
3
    04-01-1985 57.4714
4
    05-01-1985 55.3151
. .
           . . .
                    . . .
392 09-01-2017 98.6154
393 10-01-2017 93.6137
394 11-01-2017 97.3359
395 12-01-2017 114.7212
396 01-01-2018 129.4048
[397 rows x 2 columns]
```

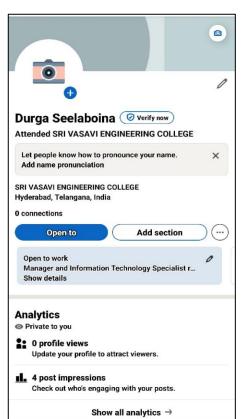
# Socjal

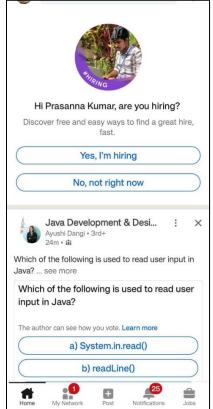


# HANDLES

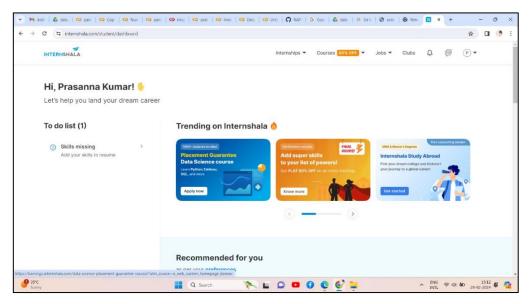


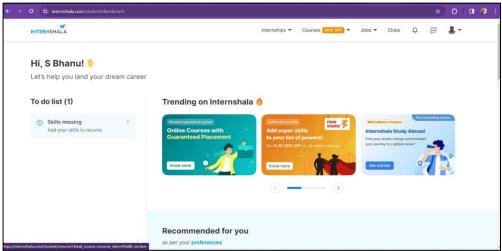


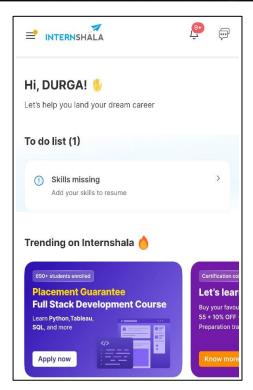




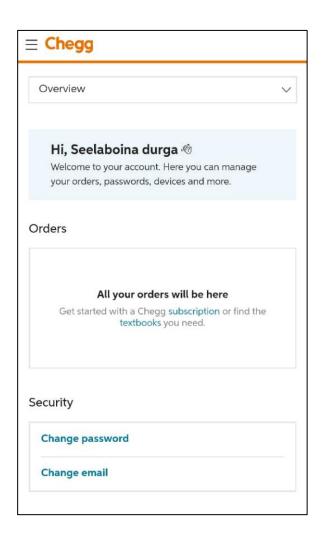


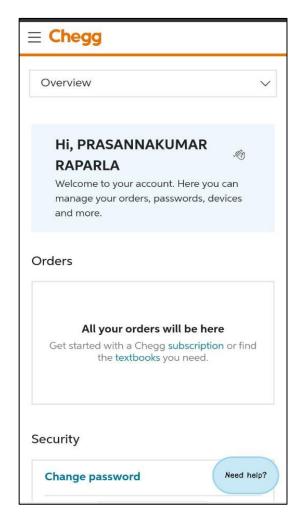


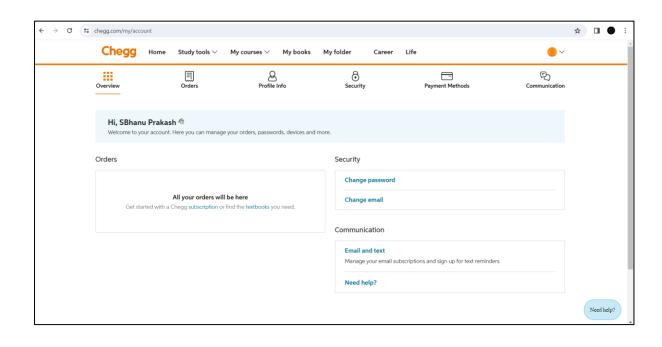




# Chegg









22A81A05I4

R.Harshitha

**TEAM-6** 

LinkedIn POSTS

**CSE-C** 



22A81A05I7

R.Prasanna Kumar



22A81A05I9

S. Mahathi



22A81A05J0

S.Bhanu Prakash



22A81A05I8

S.Navya Sri



22A81A05J1

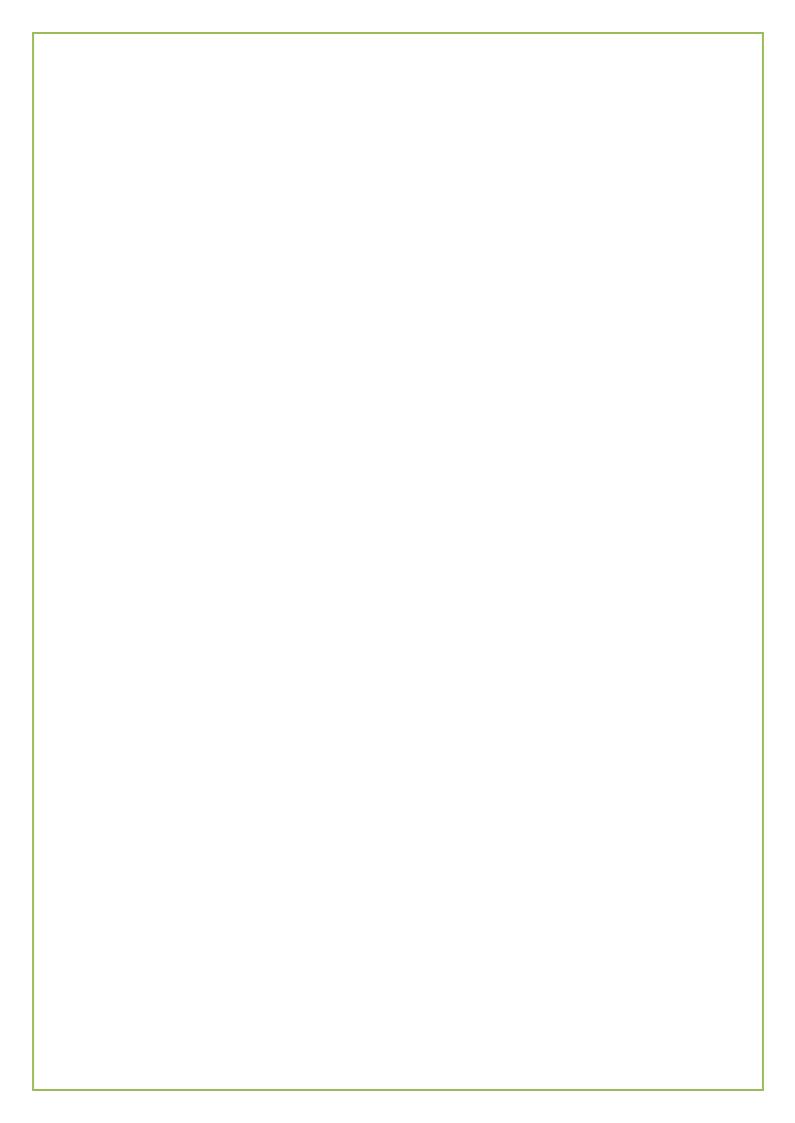
S.Durga



22A81A05J2

T.VijayRatnam





## **LINEAR -ROJECT**

[70]: import pandas as pd import numpy as np import matplotlib.pyplot as plt import sklearn

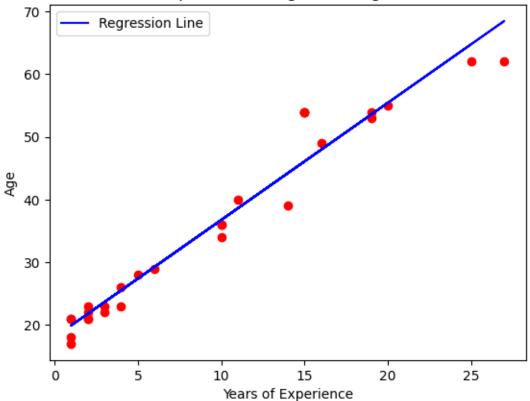
[71]: df=pd.read\_csv('/content/drive/MyDrive/dataset/lpro.csv') df

[71]:		Experience_Years	Age
	0	5	28
	1	1	21
	2	3	23
	3	2	22
	4	1	17
	5	25	62
	6	19	54
	7	2	21
	8	10	36
	9	15	54
	10	4	26
	11	6	29
	12	14	39
	13	11	40
	14	2	23
	15	4	27
	16	10	34
	17	15	54
	18	2	21
	19	10	36
	20	15	54
	21	4	26
	22	5	29
	23	1	21
	24	4	23
	25	3	22
	26	1	18
	27	27	62

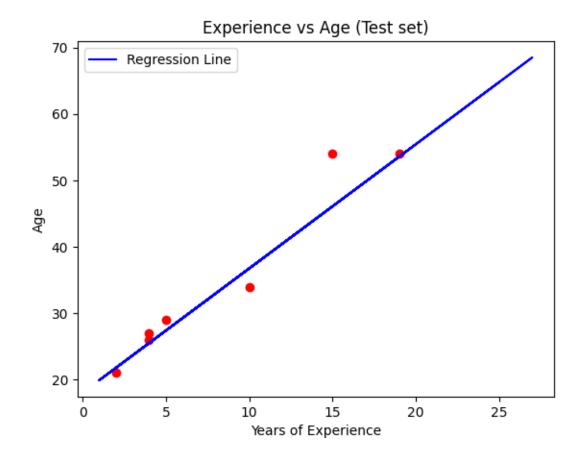
```
28
                                  19
                                         54
        29
                                   2
                                         21
        30
                                  10
                                         34
        31
                                  15
                                         54
                                         55
        32
                                  20
        33
                                  19
                                         53
        34
                                  16
                                         49
[72]:
        df.head(5)
[72] :
            Experience_Years Age
                                       28
        1
                                  1
                                       21
        2
                                  3
                                       23
                                  2
        3
                                       22
        4
                                  1
                                       17
[73] : df.isna().sum()
[73] : Experience_Years
                                    0
                                    0
        Age
        dtype: int64
[74] : X = df.iloc[:,:-1].values y =
        df.iloc[:, 1].values
[77]:
        from sklearn.model_selection import train_test_split
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, ___
          srandom_state = 0 )
[78]:
        from sklearn.linear_modelimport LinearRegression regressor =
        LinearRegression()
        print(y train) regressor.fit(X train, y train)
        [23 29 62 22 49 55 18 34 36 40 62 54 23 54 23 21 39 54 21 17 21 26 36 54
         21 53 22 28]
[78] : LinearRegression()
[79] : y_pred = regressor.predict(X_test)
        plt.scatter(X_train, y_train, color = 'red')
plt.plot(X_train, regressor.predict(X_train), color = 'blue', label='Regression_
[80] :
          sLine')
        plt.title('Experience vs Age (Training set)')
        plt.xlabel('Years of Experience')
```

plt.ylabel('Age') plt.legend() plt.show()

# Experience vs Age (Training set)



```
[83]:
          plt.scatter(X_test, y_test, color = 'red')
plt.plot(X_train, regressor.predict(X_train), color = 'blue', label='Regression_
          sLine')
plt.title('Experience vs Age (Test set)')
          plt.xlabel('Years of Experience')
          plt.ylabel('Age')
          plt.legend()
          plt.show()
```



#### WEBSCRAPPING PROJECT REPORT ON: TOP 10 YOUTUBE CHANNELS



## **DESCRIPTION:**

Youtube channels plays a vital role in society for all information like Education, gaming, entertainment etc

In this project there is information on top 10 youtube channels and their subscriber count



# WEBSCRAPPING PROJECT REPORT ON: PYTHON LISTS TABLE



## **DESCRIPTION:**

In this project there is information on some of the python list methods



#### WEBSCRAPPING PROJECT REPORT ON: CENSUS OF INDIA IN 2011



## **DESCRIPTION:**

In this project there is information on list of states with population, Sex ratio and density area in 2011.



# WEB-SCRAPPING PROJECT ON

# **INDIA.GOV.IN** website:



#### ABOUT:

The MyGov.in website serves as a platform for citizens to engage with the Indian government, facilitating two-way communication. It hosts various initiatives, discussions, surveys, and campaigns aimed at fostering citizen participation in governance. Users can access government announcements, contribute ideas, provide feedback, and collaborate on national initiatives through this interactive portal.

#### **GITHUB QR CODE:**



# WEBSCRAPPING PROJECT ON: TOP INDIAN MOVIES



#### DESCRIPTION:

Indian movies play a multifaceted role in society, blending entertainment with cultural preservation, social commentary, and economic growth, making them an integral part of both Indian and global culture.

In this project there is information on top Indian films with their gross and budget by using webscrapping



# LIST OF ALL PRIME MINISTER IN INDIA:



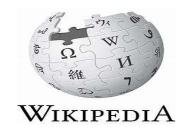
# **DESCRIPTION:**

The Prime Minister is the head of the government and leader of the Council of Ministers. He is the chief of the executive branch of the Union Government. Since India's Independence in 1947, individuals of great calibre, with the passion to work for the country, have become Prime Ministers.



## WEB-SCRAPPING PROJECT ON

## **WIKEPEDIA** website:



#### ABOUT:

South Africa has nine provinces, each with its own capital. Here is a list of the South African provincial capitals:

Eastern Cape - Bhisho

Free State - Bloemfontein

Gauteng - Johannesburg

KwaZulu-Natal - Pietermaritzburg

Limpopo - Polokwane

Mpumalanga - Nelspruit (Mbombela)

North West - Mahikeng

Northern Cape - Kimberley

Western Cape - Cape Town

These capitals serve as the administrative centers for their respective provinces.

## **GITHUB QR CODE:**



# WEBSCRAPPING PROJECT ON:TOP10 CHEAPEST CURRENCIES:



# **DESCRIPTION:**

We all have read and heard so much about the strongest currencies in the world. The British Pound Sterling, US Dollar, Swiss Franc, and Euro among others are the most well-known currencies in the world. The countries that issue these currencies are very stable, and this follows for their currencies as well. Not many of us know of the cheapest currency in the world and the countries that issue it.



# WEB-SCRAPPING PROJECT ON

# **ALLTHATGROWS** website:



#### **ABOUT**:

AllThatGrows is a comprehensive online platform offering a diverse range of high-quality seeds, bulbs, and gardening essentials. Their website provides an extensive collection of organic and heirloom seeds, along with expert gardening tips and resources. Inside, users can find detailed product information, growing guides, and a vibrant community forum to support their gardening endeavours.

## **GITHUB QR CODE:**

