Lab Excercise-08:LSTM/GRU-Based Recurrent Neural Network Construction

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Import Libraries

- **numpy**: Provides efficient support for numerical computations and array operations.
- pandas: Facilitates data manipulation and analysis with powerful data structures like DataFrames.
- matplotlib.pyplot: Enables creation of static, animated, and interactive visualizations.
- **seaborn**: Enhances data visualization with advanced statistical plots and improved aesthetics.

```
In [1]:
    import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
```

Load Dataset

1. Country Name

- **Description**: The name of the country.
- **Type**: Categorical/String.

2. Country Code

- **Description**: A unique code or abbreviation representing the country.
- Type: Categorical/String.

3. Year

- **Description**: The year for which the data is recorded.
- **Type**: Numeric/Integer.

4. Agriculture (% GDP)

- **Description**: The percentage of a country's Gross Domestic Product (GDP) derived from agriculture.
- Type: Numeric/Float.

5. Ease of Doing Business

- **Description**: An index or score representing how easy it is to do business in the country, typically based on various factors like regulatory environment, business regulations, etc.
- Type: Numeric/Float or Categorical.

6. Education Expenditure (% GDP)

- **Description**: The percentage of a country's GDP spent on education.
- **Type**: Numeric/Float.

7. Export (% GDP)

- **Description**: The percentage of a country's GDP that comes from exports.
- Type: Numeric/Float.

8. GDP

- **Description**: The Gross Domestic Product of the country, which measures the total economic output.
- **Type**: Numeric/Float.

9. Health Expenditure (% GDP)

- **Description**: The percentage of a country's GDP spent on health care.
- **Type**: Numeric/Float.

10. Import (% GDP)

- **Description**: The percentage of a country's GDP that is spent on imports.
- **Type**: Numeric/Float.

11. Industry (% GDP)

- **Description**: The percentage of a country's GDP derived from the industrial sector.
- Type: Numeric/Float.

12. Inflation Rate

- **Description**: The rate at which the general level of prices for goods and services is rising, causing purchasing power to fall.
- Type: Numeric/Float.

13. R&D

- **Description**: Expenditure on Research and Development as a percentage of GDP, or another measure of R&D investment.
- **Type**: Numeric/Float.

14. Service (% GDP)

- **Description**: The percentage of a country's GDP derived from the service sector.
- **Type**: Numeric/Float.

15. Unemployment

- **Description**: The percentage of the labor force that is unemployed and actively seeking employment.
- Type: Numeric/Float.

16. Population

- **Description**: The total number of people living in the country.
- **Type**: Numeric/Integer.

17. Land

- **Description**: The total land area of the country.
- **Type**: Numeric/Float.

18. Continent Name

- **Description**: The continent on which the country is located.
- **Type**: Categorical/String.

19. Export

- **Description**: This feature appears twice in the list; it might be duplicated or refer to different aspects of export data. Ensure consistency or clarification of this feature.
- **Type**: Numeric/Float.

20. Import

- **Description**: Similar to exports, this feature appears twice and might need clarification or correction for duplication.
- **Type**: Numeric/Float.

21. Education Expenditure

- Description: This feature also appears twice; confirm whether it's the same as earlier or a different aspect of education expenditure.
- **Type**: Numeric/Float.

22. Health Expenditure

• **Description**: Same as above, confirm the feature's duplication or intended different aspect.

• Type: Numeric/Float.

23. Net Trade

- **Description**: The difference between exports and imports as a percentage of GDP.
- Type: Numeric/Float.

24. GDP Per Capita

- **Description**: The GDP divided by the population, representing the average economic output per person.
- **Type**: Numeric/Float.

25. Population Density

- **Description**: The number of people per unit area of land (e.g., people per square kilometer).
- Type: Numeric/Float.

```
In [2]: df3 = pd.read_csv('/content/Countries.csv')
df3.shape

Out[2]: (5106, 25)
```

The dataset consists of 5106 rows and 25 columns

```
In [3]: df3.head()
```

Out[3]:

:	Country Name	Country Code	Year	Agriculture (% GDP)	Ease of Doing Business	Education Expenditure (% GDP)	Export (% GDP)	GDP	Health Expenditure (% GDP)	Import (% GDP)	•••	Population	Land	Continent Name	Exţ
	0 Afghanistan	AFG	2000	27.501127	40.717968	13.670101	NaN	1.415197e+10	10.902580	NaN		19542982.0	652860.0	Asia	1
	1 Afghanistan	AFG	2001	27.501127	40.717968	13.670101	NaN	1.415197e+10	10.902580	NaN		19688632.0	652860.0	Asia	1
	2 Afghanistan	AFG	2002	38.627892	40.717968	13.670101	NaN	3.854235e+09	9.443391	NaN		21000256.0	652860.0	Asia	1
	3 Afghanistan	AFG	2003	37.418855	40.717968	13.670101	NaN	4.539497e+09	8.941258	NaN		22645130.0	652860.0	Asia	1
	4 Afghanistan	AFG	2004	29.721067	40.717968	13.670101	NaN	5.220825e+09	9.808474	NaN		23553551.0	652860.0	Asia	1

5 rows × 25 columns

 \triangleleft

In [4]: df3.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5106 entries, 0 to 5105
Data columns (total 25 columns):
```

#	Column	Non-Null Count	Dtype				
0	Country Name	5106 non-null	object				
1	Country Code	5106 non-null	object				
2	Year	5106 non-null	int64				
3	Agriculture (% GDP)	4830 non-null	float64				
4	Ease of Doing Business	4508 non-null	float64				
5	Education Expenditure (% GDP)	4738 non-null	float64				
6	Export (% GDP)	4646 non-null	float64				
7	GDP	5037 non-null	float64				
8	Health Expenditure (% GDP)	4531 non-null	float64				
9	Import (% GDP)	4646 non-null	float64				
10	Industry (% GDP)	4853 non-null	float64				
11	Inflation Rate	4554 non-null	float64				
12	R&D	3588 non-null	float64				
13	Service (% GDP)	4807 non-null	float64				
14	Unemployment	4439 non-null	float64				
15	Population	5106 non-null	float64				
16	Land	5106 non-null	float64				
17	Continent Name	5106 non-null	object				
18	Export	4646 non-null	float64				
19	Import	4646 non-null	float64				
20	Education Expenditure	4692 non-null	float64				
21	Health Expenditure	4531 non-null	float64				
22	Net Trade	4646 non-null	float64				
23	GDP Per Capita	5037 non-null	float64				
24	Population Density	5106 non-null	float64				
types: float64(21), int64(1), object(3)							

dtypes: float64(21), int64(1), object(3)

memory usage: 997.4+ KB

df3.describe() In [5]:

Out[5]:

	Year	Agriculture (% GDP)	Ease of Doing Business	Education Expenditure (% GDP)	Export (% GDP)	GDP	Health Expenditure (% GDP)	Import (% GDP)	Industry (% GDP)	Inflation Rate	•••	Unemplo
count	5106.000000	4830.000000	4508.000000	4738.000000	4646.000000	5.037000e+03	4531.000000	4646.000000	4853.000000	4554.000000		4439.(
mean	2011.000000	10.893914	61.738665	14.458547	44.018003	3.120245e+11	6.167133	49.445204	26.315490	6.991400		8.1
std	6.633899	10.971965	13.775267	4.984259	33.173984	1.405946e+12	2.744570	30.474001	12.924200	19.858123		5.8
min	2000.000000	0.012519	19.977700	0.833360	1.571162	1.396473e+07	1.263576	1.127672	2.758632	-16.859691		0.0
25%	2005.000000	2.275972	52.919894	10.870940	23.544736	4.186073e+09	4.158750	29.401814	17.919508	1.599237		3.8
50%	2011.000000	6.979923	61.982110	13.952830	36.438987	1.777477e+10	5.639608	42.543697	24.119251	3.466447		6.5
75%	2017.000000	16.748657	72.535918	17.609406	54.543771	1.216041e+11	7.865923	60.600202	31.812769	7.288914		10.8
max	2022.000000	79.042362	87.166330	44.801800	433.836004	2.546270e+13	24.230680	429.359095	86.669555	557.201817		37.3

8 rows × 22 columns

In [6]: df3.isnull().sum()

Out[6]: **0**

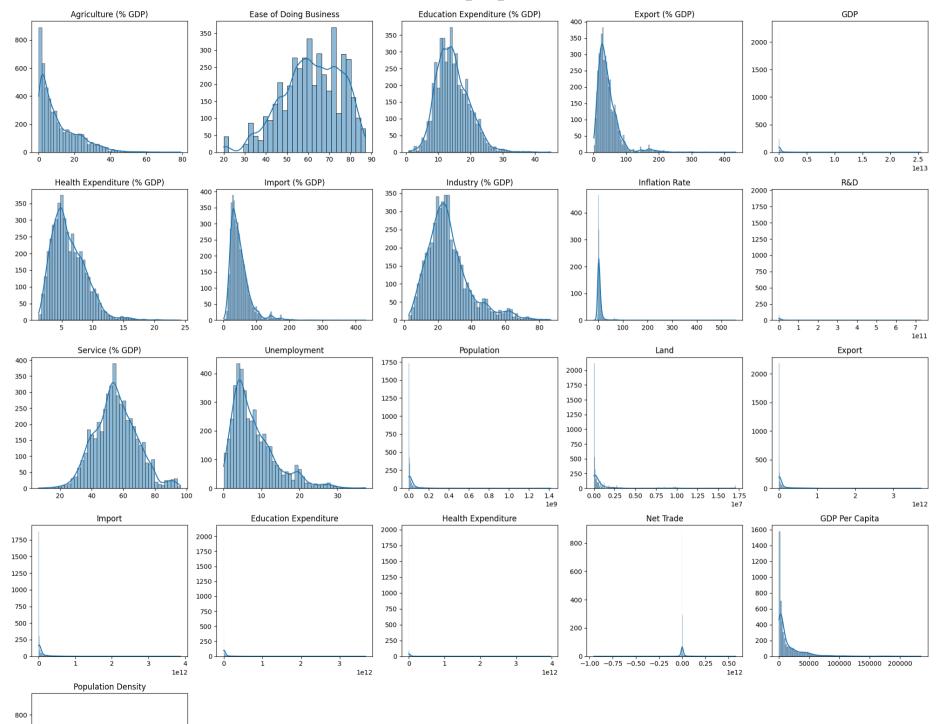
Country Name	0
Country Code	0
Year	0
Agriculture (% GDP)	276
Ease of Doing Business	598
Education Expenditure (% GDP)	368
Export (% GDP)	460
GDP	69
Health Expenditure (% GDP)	575
Import (% GDP)	460
Industry (% GDP)	253
Inflation Rate	552
R&D	1518
Service (% GDP)	299
Unemployment	667
Population	0
Land	0
Continent Name	0
Export	460
Import	460
Education Expenditure	414
Health Expenditure	575
Net Trade	460
GDP Per Capita	69

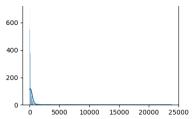
0

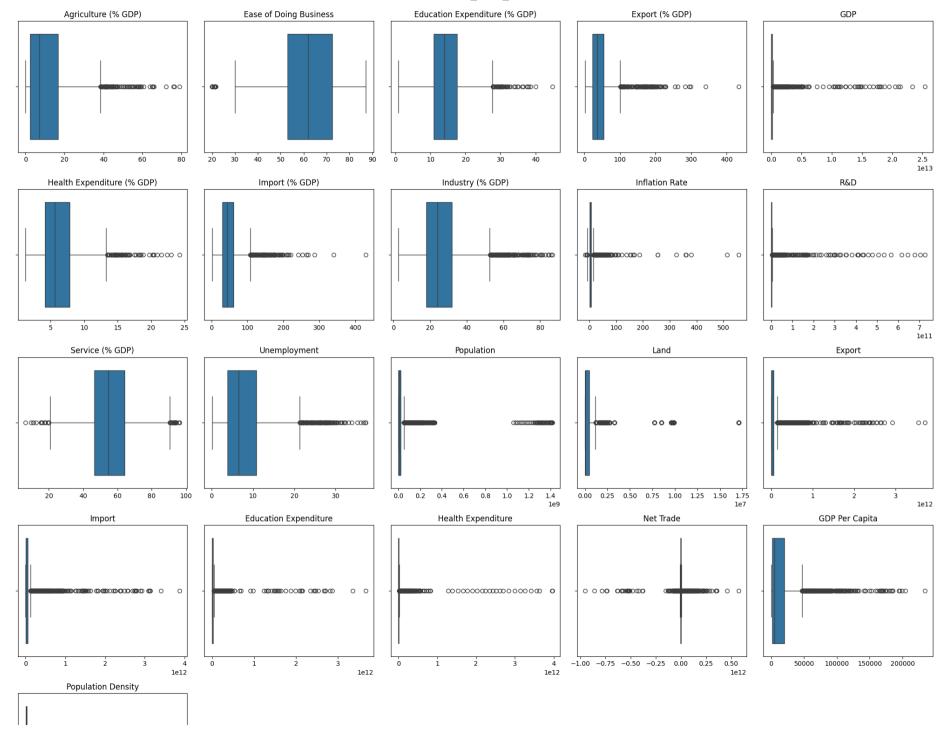
Population Density 0

dtype: int64

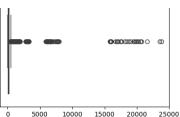
```
# List of numerical columns
In [7]:
         numerical columns = [
             'Agriculture (% GDP)', 'Ease of Doing Business', 'Education Expenditure (% GDP)',
             'Export (% GDP)', 'GDP', 'Health Expenditure (% GDP)', 'Import (% GDP)',
             'Industry (% GDP)', 'Inflation Rate', 'R&D', 'Service (% GDP)', 'Unemployment',
             'Population', 'Land', 'Export', 'Import', 'Education Expenditure',
             'Health Expenditure', 'Net Trade', 'GDP Per Capita', 'Population Density'
        # Plot histograms for each numerical column
         plt.figure(figsize=(20, 18))
        for i, col in enumerate(numerical_columns, 1):
            plt.subplot(5, 5, i)
            sns.histplot(df3[col].dropna(), kde=True)
            plt.title(col)
            plt.xlabel('')
            plt.ylabel('')
         plt.tight layout()
         plt.show()
        # Plot boxplots for each numerical column to check for outliers
        plt.figure(figsize=(20, 18))
        for i, col in enumerate(numerical columns, 1):
            plt.subplot(5, 5, i)
            sns.boxplot(x=df3[col].dropna())
            plt.title(col)
            plt.xlabel('')
        plt.tight layout()
        plt.show()
```





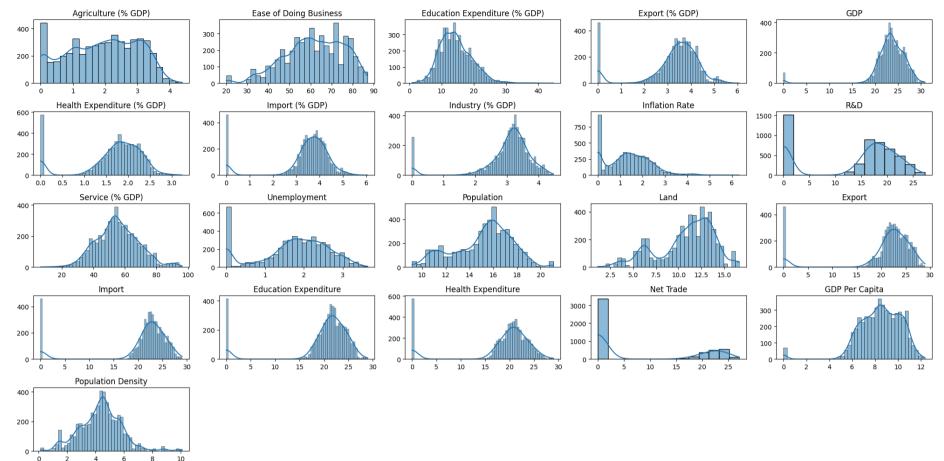


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```
In [8]: # Calculate skewness
        skewness = df3[numerical_columns].skew()
        # Transformations to reduce skewness
        # Apply log transformation for highly skewed data
        for col in skewness[abs(skewness) > 1].index:
            df3[col] = df3[col].apply(lambda x: np.log(x + 1) if x > 0 else 0)
        # Check the distribution after transformation
        plt.figure(figsize=(20, 10))
        for i, col in enumerate(numerical columns, 1):
            plt.subplot(5, 5, i)
            sns.histplot(df3[col], kde=True)
            plt.title(col)
            plt.xlabel('')
            plt.ylabel('')
        plt.tight_layout()
        plt.show()
```



```
In [9]: # Using median for imputation
median_values = {
    'Agriculture (% GDP)': df3['Agriculture (% GDP)'].median(),
    'Ease of Doing Business': df3['Ease of Doing Business'].median(),
    'Education Expenditure (% GDP)': df3['Education Expenditure (% GDP)'].median(),
    'Export (% GDP)': df3['Export (% GDP)'].median(),
    'Health Expenditure (% GDP)': df3['Health Expenditure (% GDP)'].median(),
    'Industry (% GDP)': df3['Import (% GDP)'].median(),
    'Inflation Rate': df3['Inflation Rate'].median(),
    'R&D': df3['R&D'].median(),
    'Service (% GDP)': df3['Service (% GDP)'].median(),
    'Unemployment': df3['Unemployment'].median(),
    'Net Trade': df3['Net Trade'].median(),
    'Net Trade': df3['Net Trade'].median(),
```

```
df3.fillna(median values, inplace=True)
# Columns with smaller amounts of missing data can be imputed with forward fill or backward fill
df3.fillna(method='ffill', inplace=True) # Forward fill
df3.fillna(method='bfill', inplace=True) # Backward fill
# Check if all missing values are handled
missing values post = df3.isnull().sum()
print(missing values post)
                                 0
Country Name
Country Code
                                 0
Year
Agriculture (% GDP)
Ease of Doing Business
Education Expenditure (% GDP)
Export (% GDP)
GDP
Health Expenditure (% GDP)
Import (% GDP)
Industry (% GDP)
                                 0
Inflation Rate
R&D
Service (% GDP)
Unemployment
Population
Land
Continent Name
Export
Import
Education Expenditure
Health Expenditure
Net Trade
GDP Per Capita
Population Density
dtype: int64
<ipython-input-9-75d43282897e>:19: FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a future versio
n. Use obj.ffill() or obj.bfill() instead.
 df3.fillna(method='ffill', inplace=True) # Forward fill
<ipython-input-9-75d43282897e>:20: FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a future versio
n. Use obj.ffill() or obj.bfill() instead.
  df3.fillna(method='bfill', inplace=True) # Backward fill
```

```
# List of numerical columns
In [10]:
         numerical columns = [
             'Agriculture (% GDP)', 'Ease of Doing Business', 'Education Expenditure (% GDP)',
              'Export (% GDP)', 'GDP', 'Health Expenditure (% GDP)', 'Import (% GDP)',
             'Industry (% GDP)', 'Inflation Rate', 'R&D', 'Service (% GDP)', 'Unemployment',
             'Population', 'Land', 'Export', 'Import', 'Education Expenditure',
             'Health Expenditure', 'Net Trade', 'GDP Per Capita', 'Population Density'
         # Function to identify outliers using IQR
         def identify outliers(df, col):
             Q1 = df[col].quantile(0.25)
             Q3 = df[col].quantile(0.75)
             IOR = 03 - 01
             lower bound = 01 - 1.5 * IOR
             upper bound = 03 + 1.5 * IOR
             return df[(df[col] < lower bound) | (df[col] > upper bound)]
         from scipy import stats
         # Function to identify outliers using Z-Score
         def identify outliers zscore(df, col):
             z scores = np.abs(stats.zscore(df[col].dropna()))
             return df[z scores > 3]
         # Function to handle outliers using Z-Score
         def handle outliers zscore(df, col):
             z scores = np.abs(stats.zscore(df[col].dropna()))
             df[col] = np.where(z scores > 3, df[col].median(), df[col])
         # Identify and count outliers for each column before handling
         outliers info before z = {}
         for col in numerical columns:
             outliers = identify outliers zscore(df3, col)
             outliers info before z[col] = len(outliers)
         # Print number of outliers for each column before handling
         print("Number of outliers in each column before Z-Score handling:")
         for col, count in outliers info before z.items():
             print(f"{col}: {count} outliers")
         # Handle outliers using Z-Score
         for col in numerical columns:
```

```
handle_outliers_zscore(df3, col)

# Identify and count outliers for each column after handling
outliers_info_after_z = {}
for col in numerical_columns:
    outliers = identify_outliers_zscore(df3, col)
    outliers_info_after_z[col] = len(outliers)

# Print number of outliers for each column after handling
print("\nNumber of outliers in each column after Z-Score handling:")
for col, count in outliers_info_after_z.items():
    print(f"{col}: {count} outliers")
```

Number of outliers in each column before Z-Score handling: Agriculture (% GDP): 0 outliers Ease of Doing Business: 46 outliers Education Expenditure (% GDP): 43 outliers Export (% GDP): 0 outliers GDP: 69 outliers Health Expenditure (% GDP): 0 outliers Import (% GDP): 0 outliers Industry (% GDP): 253 outliers Inflation Rate: 34 outliers R&D: 0 outliers Service (% GDP): 14 outliers Unemployment: 0 outliers Population: 0 outliers Land: 7 outliers Export: 460 outliers Import: 460 outliers Education Expenditure: 414 outliers Health Expenditure: 0 outliers Net Trade: 0 outliers GDP Per Capita: 69 outliers Population Density: 53 outliers Number of outliers in each column after Z-Score handling: Agriculture (% GDP): 0 outliers Ease of Doing Business: 0 outliers Education Expenditure (% GDP): 14 outliers Export (% GDP): 0 outliers GDP: 2 outliers Health Expenditure (% GDP): 0 outliers Import (% GDP): 0 outliers Industry (% GDP): 29 outliers Inflation Rate: 27 outliers R&D: 0 outliers Service (% GDP): 4 outliers Unemployment: 0 outliers Population: 0 outliers Land: 0 outliers Export: 1 outliers Import: 1 outliers Education Expenditure: 2 outliers Health Expenditure: 0 outliers Net Trade: 0 outliers

GDP Per Capita: 0 outliers
Population Density: 46 outliers

```
In [11]: import pandas as pd
          from sklearn.preprocessing import MinMaxScaler
          # Drop irrelevant columns
          df3 = df3.drop(columns=['Continent Name', 'Country Code'])
          # One-hot encode the 'Country Name' column
          df encoded = pd.get dummies(df3, columns=['Country Name'])
          # Identify numeric columns for normalization
          numeric cols = df encoded.select dtypes(include=['float64', 'int64']).columns
          # Exclude columns that should not be normalized
          cols to normalize = numeric cols.difference(['Year', 'GDP', 'GDP Per Capita'])
          # Initialize MinMaxScaler
          scaler = MinMaxScaler()
          # Normalize selected columns
          df encoded[cols to normalize] = scaler.fit transform(df encoded[cols to normalize])
          # Split the dataset into features and labels
          X = df encoded.drop(columns=['GDP', 'GDP Per Capita'])
          y gdp = df encoded['GDP']
         y gdp per capita = df encoded['GDP Per Capita']
          # Optional: Display the first few rows of the processed dataset
          print(X.head())
          print(y gdp.head())
          print(y gdp per capita.head())
```

```
Year Agriculture (% GDP) Ease of Doing Business \
  2000
                    0.764381
                                            0.186992
  2001
                                            0.186992
                    0.764381
2
  2002
                    0.839586
                                            0.186992
  2003
                    0.832516
                                            0.186992
                    0.781496
                                            0.186992
  2004
   Education Expenditure (% GDP)
                                  Export (% GDP) Health Expenditure (% GDP) \
0
                        0.460627
                                             0.0
                                                                     0.767258
                                             0.0
1
                        0.460627
                                                                     0.767258
2
                        0.460627
                                             0.0
                                                                     0.726743
3
                        0.460627
                                             0.0
                                                                     0.711478
4
                        0.460627
                                             0.0
                                                                     0.737387
  Import (% GDP) Industry (% GDP)
                                     Inflation Rate
                                                     R&D
0
              0.0
                                           0.456583
                           0.553659
                                                     0.0
                                           0.456583 0.0
1
              0.0
                           0.553659
2
              0.0
                           0.599201
                                           0.456583 0.0
3
                                           0.456583 0.0
              0.0
                           0.584812
4
              0.0
                           0.628714
                                           0.456583 0.0 ...
                         Country Name Uzbekistan Country Name Vanuatu \
  Country Name Uruguay
0
                  False
                                           False
                                                                  False
1
                  False
                                           False
                                                                  False
                  False
2
                                           False
                                                                  False
                  False
3
                                           False
                                                                  False
4
                  False
                                           False
                                                                  False
   Country Name Venezuela, RB Country Name Vietnam \
0
                        False
                                              False
1
                        False
                                              False
2
                        False
                                              False
3
                        False
                                              False
                        False
4
                                              False
   Country Name Virgin Islands (U.S.) Country Name West Bank and Gaza \
0
                                False
                                                                  False
                                                                  False
1
                                False
2
                                False
                                                                  False
3
                                False
                                                                  False
4
                                False
                                                                  False
   Country Name Yemen, Rep. Country Name Zambia Country Name Zimbabwe
0
                      False
                                           False
                                                                   False
```

```
1
                               False
                                                     False
                                                                            False
         2
                               False
                                                     False
                                                                            False
         3
                               False
                                                     False
                                                                            False
         4
                               False
                                                     False
                                                                            False
         [5 rows x 235 columns]
              23,373120
         1
              23,373120
              22.072438
         3
              22.236082
              22,375921
         Name: GDP, dtype: float64
              6.586373
         1
              6.578958
         2
              5.217827
         3
              5.305603
              5,405635
         Name: GDP Per Capita, dtype: float64
In [12]: # Ensure features are a numpy array
         X np = np.array(X)
In [13]: import seaborn as sns
         from sklearn.preprocessing import MinMaxScaler
          from sklearn.model selection import train test split
         from tensorflow.keras.models import Sequential
          from tensorflow.keras.layers import Dense, LSTM, Dropout
          from tensorflow.keras.optimizers import Adam
         # To ignore warnings
          import warnings
         warnings.filterwarnings("ignore")
In [14]: # Reshape the features for LSTM
         X lstm = np.reshape(X np, (X.shape[0], X.shape[1], 1)).astype('float32') # Convert to float32
          # Split data into training and testing
         X train, X test, y train, y test = train test split(X lstm, y gdp.astype('float32'), test size=0.2, random state=42) # Convert y
          # Building the LSTM Model
          model gdp = Sequential()
         model gdp.add(LSTM(50, return sequences=True, input shape=(X train.shape[1], 1)))
         model gdp.add(Dropout(0.2))
```

```
model_gdp.add(LSTM(50, return_sequences=False))
model_gdp.add(Dropout(0.2))
model_gdp.add(Dense(25))
model_gdp.add(Dense(1))

# Compile the model
model_gdp.compile(optimizer=Adam(learning_rate=0.001), loss='mean_squared_error')

# Train the model
model_gdp.fit(X_train, y_train, batch_size=32, epochs=500)

# Predicting GDP
pred_gdp = model_gdp.predict(X_test)
```

Epoch 1/500 128/128 ————————————————————————————————————	65	16ms/sten	_	1055.	247 3952
Epoch 2/500	03	101113/3 ССР		1033.	247.3332
128/128 ————	2s	18ms/step	_	loss:	9.2256
Epoch 3/500					
128/128	3s	18ms/step	-	loss:	8.7127
Epoch 4/500		•			
128/128	2s	15ms/step	-	loss:	9.2279
Epoch 5/500					
	3s	15ms/step	-	loss:	8.9232
Epoch 6/500					
	3s	15ms/step	-	loss:	8.8850
Epoch 7/500	_			-	
	3s	17ms/step	-	loss:	8.8823
Epoch 8/500	4 -	25		1	0.0724
	45	25ms/step	-	1055:	8.0/34
Epoch 9/500 128/128	26	15ms/step	_	1000	9 0599
Epoch 10/500	23	13113/3CEP	_	1033.	0.9388
•	35	15ms/step	_	1055.	8 8221
Epoch 11/500	,,,	131113/ 3 сер		1033.	0.0221
•	3s	15ms/step	_	loss:	8.3923
Epoch 12/500		, ,			
•	3s	17ms/step	-	loss:	8.4267
Epoch 13/500					
128/128	3s	19ms/step	-	loss:	8.5771
Epoch 14/500					
128/128	2s	18ms/step	-	loss:	8.7594
Epoch 15/500	_			-	
	3s	18ms/step	-	loss:	8.1593
Epoch 16/500 128/128	2-	17		1	0 6375
Epoch 17/500	25	17ms/step	-	1088:	8.63/5
	55	34ms/step	_	1055.	8 4753
Epoch 18/500	,,	э4шэ/ эсср		1033.	0.4755
•	3s	23ms/step	_	loss:	8.5389
Epoch 19/500		, с сор			
128/128	2s	18ms/step	-	loss:	8.5458
Epoch 20/500					
	2s	17ms/step	-	loss:	8.2659
Epoch 21/500					
	3s	24ms/step	-	loss:	8.1026
Epoch 22/500				_	
128/128	5s	20ms/step	-	loss:	8.4744

Epoch 23/500					
	25	15ms/step	_	loss:	8.2691
Epoch 24/500					01-01-
•	35	15ms/step	_	loss:	8.5246
Epoch 25/500					
•	2s	15ms/step	_	loss:	8.3761
Epoch 26/500		, ,			
•	3s	21ms/step	_	loss:	8.0406
Epoch 27/500					
•	2s	16ms/step	_	loss:	7.9377
Epoch 28/500					
128/128	2s	15ms/step	-	loss:	7.8197
Epoch 29/500					
128/128	2s	15ms/step	-	loss:	7.8194
Epoch 30/500					
128/128	2s	15ms/step	-	loss:	8.4309
Epoch 31/500					
128/128	3s	16ms/step	-	loss:	7.7442
Epoch 32/500					
128/128	3s	20ms/step	-	loss:	8.1259
Epoch 33/500					
128/128	5s	16ms/step	-	loss:	7.8281
Epoch 34/500					
128/128	2s	15ms/step	-	loss:	8.0249
Epoch 35/500	_			-	
128/128	35	15ms/step	-	loss:	/.//35
Epoch 36/500	2 -	22 / 1			0 2402
128/128 ————————————————————————————————————	35	22ms/step	-	loss:	8.2193
Epoch 37/500 128/128 ————————————————————————————————————	20	1Emc/ston		1000	7 0212
	25	131113/3 ceb	-	1055.	7.9213
Epoch 38/500 128/128 ————————————————————————————————————	26	1Emc/ston		1000	7 9206
Epoch 39/500	23	131113/3 ceb	-	1055.	7.0290
128/128 —————	25	15ms/sten	_	1055.	7 8206
Epoch 40/500		1311137 3 CCP		1033.	7.0200
•	25	15ms/step	_	loss:	7.5482
Epoch 41/500		133, 3 сер		1055.	, , , , , , ,
-	2s	16ms/step	_	loss:	7.8795
Epoch 42/500		, P		•	
128/128	3s	21ms/step	_	loss:	7.6330
Epoch 43/500					
128/128	4s	16ms/step	_	loss:	7.5068
Epoch 44/500		·			
128/128	2s	15ms/step	-	loss:	7.6622
		•			

Epoch 45/500					
	2s	15ms/step	-	loss:	7.4096
Epoch 46/500	_	10 / 1		-	- 2540
	25	18ms/step	-	loss:	7.3548
Epoch 47/500 128/128	3 c	20ms/step	_	1000	7 1110
Epoch 48/500	23	20113/3CEP	_	1033.	7.4440
•	2s	15ms/step	_	loss:	7,4263
Epoch 49/500		, с сор			
128/128	3s	15ms/step	-	loss:	7.3942
Epoch 50/500					
128/128	3s	15ms/step	-	loss:	7.0874
Epoch 51/500	_			-	
128/128	2s	15ms/step	-	loss:	7.3641
Epoch 52/500 128/128	26	20ms /stan		10001	6 0077
Epoch 53/500	55	20ms/step	-	1022:	0.90//
128/128	2s	17ms/step	_	loss:	6.9507
Epoch 54/500		, с сор			
128/128	2s	15ms/step	_	loss:	6.9826
Epoch 55/500					
128/128	3s	15ms/step	-	loss:	7.1061
Epoch 56/500					
	3s	19ms/step	-	loss:	7.3396
Epoch 57/500 128/128	26	20ms /stan		10001	c 9022
Epoch 58/500	55	20ms/step	-	1022:	0.8923
128/128	55	16ms/sten	_	loss:	6.9270
Epoch 59/500	,,,	1011137 3 сер		1033.	0.3270
128/128	2s	15ms/step	-	loss:	6.8454
Epoch 60/500					
	3s	15ms/step	-	loss:	6.7574
Epoch 61/500				_	
	2s	18ms/step	-	loss:	7.1090
Epoch 62/500 128/128	2.	19ms/step		1000	6 00/1
Epoch 63/500	25	19111S/Step	-	1055.	0.9041
128/128	2s	15ms/step	_	loss:	6.4952
Epoch 64/500					
•	3s	15ms/step	-	loss:	6.6987
Epoch 65/500					
	2s	15ms/step	-	loss:	6.8577
Epoch 66/500				_	
128/128	3s	15ms/step	-	loss:	6.5151

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Epoch 67/500	2 -	24 / 1		1	6 5754
128/128 — — — — Epoch 68/500	35	21ms/step	-	TOSS:	6.5/54
•	25	15ms/step	_	1055.	6 4001
Epoch 69/500	23	15/1/3 сер		1033.	0.4001
128/128	3s	19ms/step	_	loss:	6.4457
Epoch 70/500					
128/128	2s	15ms/step	-	loss:	6.5381
Epoch 71/500					
	3s	15ms/step	-	loss:	6.5283
Epoch 72/500					
	3s	22ms/step	-	loss:	6.4241
Epoch 73/500		16 / 1			6 0043
	45	16ms/step	-	loss:	6.0843
Epoch 74/500 128/128	20	1Emc/ston		1000	6 2222
Epoch 75/500	25	15ms/step	-	1055.	0.3223
128/128	25	15ms/step	_	loss:	6.4547
Epoch 76/500		133, 3 ccp		1055.	0.1517
128/128 ————	3s	18ms/step	_	loss:	6.2727
Epoch 77/500					
128/128	2s	19ms/step	-	loss:	6.4767
Epoch 78/500					
128/128	2s	15ms/step	-	loss:	6.4941
Epoch 79/500	_	4- / .		-	
128/128	25	15ms/step	-	loss:	6.2451
Epoch 80/500 128/128	20	15ms/step		1000	6 0220
Epoch 81/500	23	131113/3CEP	_	1033.	0.0320
128/128	3s	16ms/step	_	loss:	6.3162
Epoch 82/500		, ,			
128/128	3s	20ms/step	-	loss:	6.2849
Epoch 83/500					
128/128	2s	17ms/step	-	loss:	6.3094
Epoch 84/500	_			-	
128/128	2s	15ms/step	-	loss:	6.3142
Epoch 85/500	2.0	1Emc/ston		1000	E 0040
128/128 ————————————————————————————————————	22	יווכד / sreb	-	TO22;	J. 7747
	25	15ms/step	_	loss:	6.0751
Epoch 87/500					J. J. J. L
	2s	15ms/step	_	loss:	6.1884
Epoch 88/500					
128/128	3s	22ms/step	-	loss:	6.0339

Epoch 89/500					
128/128	4s	17ms/step	_	loss:	5.8235
Epoch 90/500		-,			
128/128	2s	15ms/step	_	loss:	6.0537
Epoch 91/500		, ,			
	2s	15ms/step	_	loss:	5.9937
Epoch 92/500		·			
	3s	19ms/step	-	loss:	6.3718
Epoch 93/500					
128/128	2s	19ms/step	-	loss:	5.9809
Epoch 94/500					
128/128	2s	15ms/step	-	loss:	5.7018
Epoch 95/500					
128/128	2s	15ms/step	-	loss:	5.9216
Epoch 96/500					
	2s	15ms/step	-	loss:	6.1651
Epoch 97/500					
	2s	15ms/step	-	loss:	5.9241
Epoch 98/500					
128/128	2s	19ms/step	-	loss:	5.9818
Epoch 99/500				_	
128/128	2s	19ms/step	-	loss:	5.8953
Epoch 100/500	_			-	
128/128	2s	16ms/step	-	loss:	5.9666
Epoch 101/500	2 -	45 / 1		,	E 0004
128/128	35	15ms/step	-	1055:	5.8021
Epoch 102/500 128/128	2.	15/		1	F 7020
Epoch 103/500	35	15ms/step	-	1088:	5.7929
128/128	26	16ms/stan	_	1000	5 7702
Epoch 104/500	23	Tollis/ Scep	_	1033.	3.7702
128/128	3 c	21ms/sten	_	1055.	5 8305
Epoch 105/500	23	211113/3сср		1033.	3.0303
128/128 ————	2s	15ms/step	_	loss:	5.9620
Epoch 106/500					3,7020
•	2s	15ms/step	_	loss:	5.8931
Epoch 107/500		, с сер			
128/128	3s	15ms/step	_	loss:	5.9306
Epoch 108/500		'			
•	2s	15ms/step	-	loss:	5.7494
Epoch 109/500		·			
	3s	20ms/step	-	loss:	5.7913
Epoch 110/500					
128/128	2s	18ms/step	-	loss:	5.6870

Epoch 111/500					
	25	15ms/step	_	1055.	5 1610
Epoch 112/500		1311137 3 CCP		1033.	3.1010
	35	15ms/step	_	loss:	2.0513
Epoch 113/500					_,,,,
	3s	16ms/step	_	loss:	1.3885
Epoch 114/500		,			
•	2s	16ms/step	_	loss:	1.4495
Epoch 115/500		, ,			
•	3s	22ms/step	_	loss:	1.4570
Epoch 116/500					
128/128	2s	15ms/step	-	loss:	0.9684
Epoch 117/500					
128/128	2s	15ms/step	-	loss:	1.0942
Epoch 118/500					
128/128	3s	15ms/step	-	loss:	0.9170
Epoch 119/500					
	2s	15ms/step	-	loss:	0.9143
Epoch 120/500					
	2s	18ms/step	-	loss:	1.2692
Epoch 121/500					
128/128	3s	20ms/step	-	loss:	1.0012
Epoch 122/500					
128/128	5s	16ms/step	-	loss:	1.1030
Epoch 123/500	_			-	
128/128	2s	15ms/step	-	loss:	1.3179
Epoch 124/500	_	4- / /		-	4 0040
128/128	25	15ms/step	-	loss:	1.0048
Epoch 125/500 128/128	2.	20ms /ston		1000.	0 7250
	55	zoms/step	-	1055:	0.7350
Epoch 126/500 128/128	20	17mc/s+on		1000	0 6002
Epoch 127/500	25	1/1115/5ceb	-	1055.	0.0992
128/128	25	15ms/sten	_	1055.	0 6867
Epoch 128/500	23	151113/3сср		1033.	0.0007
•	35	15ms/step	_	loss:	0.6654
Epoch 129/500	-	233, 3 ccp		1055.	0.005
128/128	3s	15ms/step	_	loss:	0.8890
Epoch 130/500		, _F			
•	2s	17ms/step	_	loss:	0.8227
Epoch 131/500					
•	3s	20ms/step	-	loss:	0.7960
Epoch 132/500		·			
	5s	16ms/step	-	loss:	0.8292

Epoch 133/500					
-	2s	15ms/step	_	loss:	0.6337
Epoch 134/500					
128/128	2s	15ms/step	-	loss:	0.6284
Epoch 135/500					
	2s	17ms/step	-	loss:	0.7096
Epoch 136/500					
128/128	3s	20ms/step	-	loss:	0.5391
Epoch 137/500	_	4- / /		-	
128/128	25	15ms/step	-	loss:	0.6609
Epoch 138/500	2-	15/		1	0 5407
128/128 ————————————————————————————————————	25	15ms/step	-	1088:	0.5487
Epoch 139/500 128/128	26	15ms/step	_	1000	0 6801
Epoch 140/500	23	131113/3 CEP	_	1033.	0.0001
128/128	25	15ms/step	_	1055.	0 8296
Epoch 141/500		1311137 3 CCP		1033.	0.0250
128/128 ————	2s	17ms/step	_	loss:	0.8403
Epoch 142/500		, ,			
128/128	3s	20ms/step	_	loss:	0.5187
Epoch 143/500					
128/128	2s	15ms/step	-	loss:	1.4689
Epoch 144/500					
128/128	2s	15ms/step	-	loss:	0.5767
Epoch 145/500				_	
128/128	3s	15ms/step	-	loss:	0.5224
Epoch 146/500	_			-	
128/128 ————————————————————————————————————	35	16ms/step	-	Toss:	0.4421
Epoch 147/500 128/128	3 c	21ms/step	_	1000	0 1861
Epoch 148/500	23	ZIIIS/Step	-	1055.	0.4004
128/128	55	16ms/step	_	1055.	0 4780
Epoch 149/500	,,,	1011137 3 сер		1033.	0.4700
128/128 ————	2s	15ms/step	_	loss:	0.8829
Epoch 150/500					
-	3s	15ms/step	-	loss:	2.2255
Epoch 151/500					
128/128	3s	20ms/step	-	loss:	0.4465
Epoch 152/500					
	2s	18ms/step	-	loss:	0.4805
Epoch 153/500	_			-	
	2 s	15ms/step	-	loss:	0.9332
Epoch 154/500	_	45 / .			0 5405
128/128	3s	15ms/step	-	Toss:	0.5483

Epoch 155/500 128/128 ————————————————————————————————————	26	15ms/step	_	10551	0 5712
Epoch 156/500	23	13113/3CEP	_	1033.	0.3/12
•	3s	17ms/step	_	loss:	0.4057
Epoch 157/500		,,			
•	3s	20ms/step	-	loss:	0.4269
Epoch 158/500					
	2s	15ms/step	-	loss:	0.3892
Epoch 159/500	_			-	
128/128	25	15ms/step	-	loss:	0.3904
Epoch 160/500 128/128	2.0	15ms/step		1000	0 1600
Epoch 161/500	25	131118/Steb	-	1055.	0.4000
128/128	3s	15ms/step	_	loss:	0.3522
Epoch 162/500		,			
128/128	3s	21ms/step	-	loss:	0.5979
Epoch 163/500					
128/128	5s	17ms/step	-	loss:	4.7109
Epoch 164/500	_			-	
128/128 ————————————————————————————————————	2s	16ms/step	-	loss:	0.7212
Epoch 165/500 128/128 ————————————————————————————————————	26	15ms/step	_	1000	0 5770
Epoch 166/500	23	131113/3cep	_	1033.	0.3770
128/128	2s	16ms/step	_	loss:	0.4874
Epoch 167/500		,			
128/128	3s	21ms/step	-	loss:	0.4519
Epoch 168/500					
128/128	2s	15ms/step	-	loss:	0.4520
Epoch 169/500	•	45 / 1		,	0 4770
128/128 ————————————————————————————————————	25	15ms/step	-	loss:	0.4//0
Epoch 170/500 128/128	25	16ms/step	_	1055.	a 4a24
Epoch 171/500	23	1011137 3 сер		1033.	0.4024
128/128	3s	15ms/step	-	loss:	0.3816
Epoch 172/500					
	3s	19ms/step	-	loss:	0.3607
Epoch 173/500				_	
128/128	2s	19ms/step	-	loss:	0.3557
Epoch 174/500 128/128 ————————————————————————————————————	25	15ms/step		1000	0 3654
Epoch 175/500	25	ביווכד / sreb	-	1022;	0.3034
•	2s	15ms/step	_	loss:	0.3367
Epoch 176/500		, F		•	
•	3s	16ms/step	-	loss:	0.3259

Epoch 177/500	2-	16		1	0 2502
128/128 ————————————————————————————————————	55	16ms/step	-	1055:	0.3503
•	35	22ms/step	_	loss	0 4251
Epoch 179/500	,,,	221137 3 6 6 7		1033.	0.4231
•	4s	16ms/step	_	loss:	0.3659
Epoch 180/500					
128/128	2s	15ms/step	-	loss:	0.4946
Epoch 181/500					
128/128	2s	15ms/step	-	loss:	0.3523
Epoch 182/500					
128/128	2s	17ms/step	-	loss:	0.3981
Epoch 183/500	_			-	
128/128	3s	21ms/step	-	loss:	0.3205
Epoch 184/500	- -	16/-		1	0 2764
128/128 ————————————————————————————————————	55	16ms/step	-	1088:	0.3/64
128/128	25	15ms/step	_	1055.	0 3310
Epoch 186/500	23	151113/3сср		1033.	0.5510
128/128	3s	15ms/step	_	loss:	0.2923
Epoch 187/500		, с сер			
128/128	3s	21ms/step	-	loss:	0.3115
Epoch 188/500					
128/128	5s	16ms/step	-	loss:	0.3223
Epoch 189/500					
128/128	2s	15ms/step	-	loss:	0.2894
Epoch 190/500	_			_	
128/128	2s	15ms/step	-	loss:	0.3301
Epoch 191/500 128/128 ————————————————————————————————————	26	21 ms /s+on		10001	0 2706
Epoch 192/500	55	21ms/step	-	1055:	0.2700
128/128	25	16ms/step	_	1055.	a 2777
Epoch 193/500	23	1011137 3 сер		1033.	0.2///
128/128 ————	2s	16ms/step	_	loss:	0.5085
Epoch 194/500		, ,			
•	2s	15ms/step	-	loss:	0.2466
Epoch 195/500					
128/128	2s	15ms/step	-	loss:	0.2453
Epoch 196/500				_	
	3s	16ms/step	-	loss:	0.2750
Epoch 197/500	2.	20		1	0 2217
	35	20ms/step	-	1022:	v.231/
Epoch 198/500 128/128 ————————————————————————————————————	25	15ms/step		1000	0 2760
120/120	25	Tollis/sceb	-	1022;	v.2/08

Epoch 199/500	2-	45/-t		1	0 2254
128/128 ————————————————————————————————————	25	15ms/step	-	1088:	0.2254
Epoch 200/500 128/128 ————————————————————————————————————	3s	16ms/step	_	loss:	0.3441
Epoch 201/500		, с сер			
128/128	2s	15ms/step	-	loss:	0.2810
Epoch 202/500					
128/128	3s	21ms/step	-	loss:	0.2543
Epoch 203/500					
128/128	2s	15ms/step	-	loss:	0.2755
Epoch 204/500	_	4- / /		-	4 0450
128/128	3s	15ms/step	-	loss:	1.8659
Epoch 205/500	2.0	16mc/ston		1000	0 2060
128/128 ————————————————————————————————————	23	16ms/step	-	1055.	0.3009
128/128	25	15ms/step	_	1055.	0 2313
Epoch 207/500		13m3/ 3ccp		1033.	0.2313
128/128	3s	20ms/step	_	loss:	0.3071
Epoch 208/500		·			
128/128	2s	17ms/step	-	loss:	0.2141
Epoch 209/500					
128/128	2s	15ms/step	-	loss:	0.2417
Epoch 210/500	_			-	
128/128	2s	16ms/step	-	loss:	0.2879
Epoch 211/500 128/128	26	16ms/step		1000	0 2166
Epoch 212/500	23	Tollis/ Scep	_	1033.	0.2100
128/128	2s	16ms/step	_	loss:	0.2696
Epoch 213/500		,			
128/128	3s	21ms/step	-	loss:	0.2087
Epoch 214/500					
128/128	2s	18ms/step	-	loss:	2.3168
Epoch 215/500	•	16 / 1			0 2056
128/128 ————————————————————————————————————	25	16ms/step	-	loss:	0.2956
Epoch 216/500 128/128	26	16ms/step	_	1000	0 2767
Epoch 217/500	23	101113/3 ССР		1033.	0.2/0/
128/128 ————	3s	15ms/step	_	loss:	0.2294
Epoch 218/500					
128/128	3s	17ms/step	-	loss:	0.2534
Epoch 219/500					
	3s	21ms/step	-	loss:	0.2118
Epoch 220/500	_				
128/128	5s	16ms/step	-	loss:	0.1910

Epoch 221/500					
128/128	2s	15ms/step	-	loss:	0.2223
Epoch 222/500					
	2s	16ms/step	-	loss:	0.2106
Epoch 223/500	2-	20 / - +		1	0 1004
	35	20ms/step	-	loss:	0.1994
Epoch 224/500 128/128 ————————————————————————————————————	26	10mc/ston		1000	a 2002
Epoch 225/500	25	19ms/step	-	1055.	0.2003
128/128	2s	16ms/step	_	loss:	0.1985
Epoch 226/500		,			
128/128	3s	16ms/step	_	loss:	0.7087
Epoch 227/500		·			
128/128	2s	16ms/step	-	loss:	0.7216
Epoch 228/500					
128/128	2s	15ms/step	-	loss:	0.3582
Epoch 229/500	2-	22		1	0 2005
128/128 ————————————————————————————————————	35	22ms/step	-	TOSS:	0.2885
Epoch 230/500 128/128 ————————————————————————————————————	Λc	17ms/step	_	1000	0 3033
Epoch 231/500	73	171113/3 сер		1033.	0.5055
128/128 ————	2s	16ms/step	_	loss:	0.2793
Epoch 232/500					
128/128	2s	16ms/step	-	loss:	0.2871
Epoch 233/500					
128/128	3s	18ms/step	-	loss:	0.3209
Epoch 234/500	_			-	
128/128 ————————————————————————————————————	35	20ms/step	-	loss:	0.263/
Epoch 235/500 128/128	25	15ms/step	_	1055.	0 3171
Epoch 236/500	23	13/13/ 3 сер		1033.	0.51/1
128/128 ————	2s	16ms/step	_	loss:	0.2791
Epoch 237/500					
128/128	2s	16ms/step	-	loss:	0.2764
Epoch 238/500					
	2s	16ms/step	-	loss:	0.2006
Epoch 239/500	2 -	20 / 1			0 2204
128/128 ————————————————————————————————————	35	20ms/step	-	loss:	0.2284
Epoch 240/500 128/128	5c	17ms/step	_	1000	0 2068
Epoch 241/500	,,	1/1113/3ceb	_	1033.	0.2000
-	2s	15ms/step	_	loss:	0.1964
Epoch 242/500					
128/128	3s	15ms/step	-	loss:	0.2925

Epoch 243/500					
	25	19ms/step	_	loss:	0.2141
Epoch 244/500		13.113, 3 ccp		1055.	0.22.2
	25	19ms/step	_	loss:	0.2255
Epoch 245/500					011100
	2s	16ms/step	_	loss:	0.1864
Epoch 246/500		,			
•	3s	15ms/step	_	loss:	0.1811
Epoch 247/500		, ,			
•	2s	15ms/step	_	loss:	0.1914
Epoch 248/500		·			
128/128	3s	17ms/step	_	loss:	0.1779
Epoch 249/500		·			
128/128	3s	20ms/step	-	loss:	0.2008
Epoch 250/500					
128/128	2s	16ms/step	-	loss:	0.2364
Epoch 251/500					
128/128	3s	16ms/step	-	loss:	0.2451
Epoch 252/500					
	2s	16ms/step	-	loss:	0.2433
Epoch 253/500					
	3s	16ms/step	-	loss:	0.1773
Epoch 254/500					
128/128	3s	21ms/step	-	loss:	0.2410
Epoch 255/500				_	
128/128	5s	17ms/step	-	loss:	0.2194
Epoch 256/500	_			_	
128/128	2s	16ms/step	-	loss:	0.1612
Epoch 257/500	٦-	16		1	0 1077
128/128	35	16ms/step	-	Toss:	0.19//
Epoch 258/500	2-	20/		1	0 1600
128/128 ————————————————————————————————————	35	Zoms/step	-	1088:	0.1680
128/128 —————	26	19mc/c+on		1000	A 10EE
Epoch 260/500	23	Tollis/ 2 ceb	-	1055.	0.1033
•	2¢	16ms/step	_	1000	0 9851
Epoch 261/500	23	тошз/ з сер		1033.	0.5054
128/128	35	16ms/sten	_	1055.	0 1689
Epoch 262/500	23	_оэ, эсср		1000.	3.1003
•	25	16ms/step	_	loss:	0.1570
Epoch 263/500		_55, 5 ccp			3.23.0
•	3s	17ms/step	_	loss:	0.1530
Epoch 264/500		-, P		•	
	3s	20ms/step	_	loss:	0.1320
-		, F		•	

Epoch 265/500					
•	5s	17ms/step	_	loss:	0.1310
Epoch 266/500		, ,			
-	2s	16ms/step	_	loss:	0.1544
Epoch 267/500		·			
128/128	3s	16ms/step	-	loss:	0.1409
Epoch 268/500					
128/128	3s	21ms/step	-	loss:	0.1613
Epoch 269/500				_	
128/128	5s	17ms/step	-	loss:	0.1503
Epoch 270/500	_			-	0 4550
128/128 ————————————————————————————————————	25	16ms/step	-	loss:	0.15/0
Epoch 271/500 128/128 ————————————————————————————————————	20	16ms/step		1000	a 2120
Epoch 272/500	25	10IIIS/Steb	-	1055.	0.2120
128/128	3¢	21ms/step	_	1055.	a 1319
Epoch 273/500	,,	211113/300р		1033.	0.1313
128/128 ————	5s	17ms/step	_	loss:	0.1525
Epoch 274/500		, ,			
128/128	2s	15ms/step	_	loss:	0.1928
Epoch 275/500		·			
128/128	3s	15ms/step	-	loss:	0.1589
Epoch 276/500					
128/128	2s	19ms/step	-	loss:	0.1292
Epoch 277/500				_	
128/128	3s	19ms/step	-	loss:	0.1819
Epoch 278/500	•	16 / 1			F 2022
128/128 ————————————————————————————————————	25	16ms/step	-	loss:	5.3923
Epoch 279/500 128/128	26	16ms/step	_	1000	0 1050
Epoch 280/500	23	Tollis/ Scep	_	1033.	0.4030
128/128	25	15ms/step	_	loss:	0.3133
Epoch 281/500		133, 3 сер		1055.	0.3233
128/128 ————	2s	16ms/step	_	loss:	0.2962
Epoch 282/500		·			
128/128	3s	22ms/step	-	loss:	0.2179
Epoch 283/500					
128/128	2s	17ms/step	-	loss:	0.2218
Epoch 284/500				_	
	2s	16ms/step	-	loss:	0.2255
Epoch 285/500	2 -	16		1 -	0 1700
	35	16ms/step	-	Toss:	o.1798
Epoch 286/500	2-	1 Cm = / = + = :=		1	0 1021
128/128	25	16ms/step	-	TOSS:	0.1831

Epoch 287/500	_	10 / 1		-	0.4600
	35	19ms/step	-	loss:	0.1623
Epoch 288/500 128/128 ————————————————————————————————————	26	19ms/step		1000	0 2101
Epoch 289/500	23	191113/3CEP	_	1033.	0.2101
•	2s	16ms/step	_	loss:	0.1507
Epoch 290/500		,,			
•	2s	16ms/step	_	loss:	0.1995
Epoch 291/500		·			
128/128	3s	16ms/step	-	loss:	0.1562
Epoch 292/500					
128/128	2s	16ms/step	-	loss:	0.1680
Epoch 293/500				_	
128/128	3s	21ms/step	-	loss:	0.2162
Epoch 294/500	_	47 / 1		,	0 4543
128/128 ————————————————————————————————————	58	17ms/step	-	loss:	0.1513
Epoch 295/500 128/128 ————————————————————————————————————	26	16ms/step	_	1000	0 1990
Epoch 296/500	23	Tollis/ 2 ceb	-	1055.	0.1000
128/128	35	16ms/step	_	loss	0 2669
Epoch 297/500	,,,	1011137 3 сер		1033.	0.2003
128/128 ————	4s	23ms/step	_	loss:	0.1419
Epoch 298/500					
128/128	2s	16ms/step	-	loss:	0.1424
Epoch 299/500					
128/128	3s	16ms/step	-	loss:	0.1493
Epoch 300/500					
128/128	3s	15ms/step	-	loss:	0.1665
Epoch 301/500	•	16 / 1		,	0 1011
128/128 ————————————————————————————————————	25	16ms/step	-	loss:	0.1811
Epoch 302/500 128/128 ————————————————————————————————————	2 c	21ms/step		1000	0 1002
Epoch 303/500	25	ZIIIS/Step	-	1055.	0.1903
128/128	45	16ms/step	_	loss:	0.1631
Epoch 304/500		_oo, o cop			011001
•	2s	16ms/step	_	loss:	0.3680
Epoch 305/500		·			
128/128	2s	16ms/step	-	loss:	0.2080
Epoch 306/500					
	2s	16ms/step	-	loss:	0.1444
Epoch 307/500	_	22 / /		,	0.4000
	35	22ms/step	-	Toss:	0.1900
Epoch 308/500	4-	17mc/-+		1000	0 1617
128/128	45	17ms/step	-	TOSS:	η.161/

Epoch 309/500					
128/128	2s	16ms/step	-	loss:	0.4335
Epoch 310/500					
	2s	15ms/step	-	loss:	0.1432
Epoch 311/500	_			_	
	3s	21ms/step	-	loss:	0.1358
Epoch 312/500	•	47 / 1			0 4272
	25	17ms/step	-	loss:	0.13/2
Epoch 313/500 128/128	26	16ms/step	_	1000	0 11/13
Epoch 314/500	23	Tollis/ Scep	_	1033.	0.1145
128/128	35	16ms/step	_	1055.	0 1265
Epoch 315/500	"	1011137 3 сер		1033.	0.1203
128/128 ————	3s	16ms/step	_	loss:	0.1608
Epoch 316/500					
128/128	2s	19ms/step	-	loss:	0.2501
Epoch 317/500					
128/128	3s	19ms/step	-	loss:	0.1946
Epoch 318/500					
128/128	2s	16ms/step	-	loss:	0.1471
Epoch 319/500	_			-	
128/128	25	16ms/step	-	loss:	0.1652
Epoch 320/500	2-	16/		1	0 1007
128/128 ————————————————————————————————————	38	16ms/step	-	1088:	0.1887
128/128	3¢	17ms/step	_	1055.	0 1460
Epoch 322/500	"	17 m3/ 3 ccp		1033.	0.1400
128/128 ————	3s	22ms/step	_	loss:	0.1568
Epoch 323/500		-,			
128/128	2s	16ms/step	-	loss:	0.1373
Epoch 324/500					
128/128	2s	16ms/step	-	loss:	0.1731
Epoch 325/500					
	3s	16ms/step	-	loss:	0.1378
Epoch 326/500	_			-	
	2s	16ms/step	-	loss:	0.5589
Epoch 327/500 128/128 ————————————————————————————————————	2.0	10mc/ston		1000	A 1E01
Epoch 328/500	23	19111S/Scep	-	1055.	0.1361
	35	20ms/step	_	1055.	0 1236
Epoch 329/500	در	20113/3 CCP		1033.	J. 1250
-	2s	16ms/step	_	loss:	0.1382
Epoch 330/500					
	2s	15ms/step	-	loss:	0.1357

Epoch 331/500					
	3s	15ms/step	_	loss:	0.1590
Epoch 332/500					
128/128	3s	15ms/step	-	loss:	0.1310
Epoch 333/500					
	3s	22ms/step	-	loss:	0.1048
Epoch 334/500					
	2s	16ms/step	-	loss:	0.3335
Epoch 335/500	_			-	0 1010
128/128	25	16ms/step	-	loss:	0.1249
Epoch 336/500	2-	15/		1	0 1256
128/128 ————————————————————————————————————	35	15ms/step	-	1088:	0.1256
Epoch 337/500 128/128	3 c	16ms/step	_	1000	0 1039
Epoch 338/500	23	Tollis/ Scep	_	1033.	0.1030
128/128	25	19ms/step	_	1055.	0 1511
Epoch 339/500		1311137 3 CCP		1033.	0.1311
128/128 ————	2s	19ms/step	_	loss:	0.1678
Epoch 340/500		, ,			
128/128	2s	16ms/step	_	loss:	0.1261
Epoch 341/500		·			
128/128	2s	16ms/step	-	loss:	0.1508
Epoch 342/500					
128/128	2s	16ms/step	-	loss:	0.1957
Epoch 343/500				_	
128/128	3s	16ms/step	-	loss:	1.4057
Epoch 344/500	_	04 / /		-	0 4004
128/128 ————————————————————————————————————	35	21ms/step	-	loss:	0.1281
Epoch 345/500 128/128	26	17ms/step	_	1000	0 1716
Epoch 346/500	23	1/11/3/3 CEP	_	1033.	0.1/10
128/128	25	16ms/step	_	1055.	0 1345
Epoch 347/500		1011137 3 сер		1033.	0.15-5
-	3s	16ms/step	_	loss:	0.1377
Epoch 348/500					
-	3s	16ms/step	-	loss:	0.1248
Epoch 349/500					
128/128	3s	22ms/step	-	loss:	0.1273
Epoch 350/500					
	4s	17ms/step	-	loss:	0.1068
Epoch 351/500				_	
	2s	16ms/step	-	loss:	0.1153
Epoch 352/500	_			-	
128/128	2s	16ms/step	-	loss:	0.8932

Epoch 353/500 128/128 —————	35	19ms/step	_	loss:	0.1225
Epoch 354/500					011111
128/128	3s	21ms/step	-	loss:	0.1261
Epoch 355/500					
	2s	16ms/step	-	loss:	0.1092
Epoch 356/500 128/128 ————————————————————————————————————	2.0	16ms/step		1055	0 1175
Epoch 357/500	23	Tollis/Step	-	1055.	0.11/3
•	2s	16ms/step	_	loss:	0.1112
Epoch 358/500					
	2s	16ms/step	-	loss:	0.1084
Epoch 359/500	_	04 / 1		,	0 1100
128/128 ————————————————————————————————————	35	21ms/step	-	loss:	0.1183
Epoch 360/500 128/128 ————————————————————————————————————	25	17ms/step	_	1055.	a 1381
Epoch 361/500		17 m3/ 3 ccp		1033.	0.1301
128/128	2s	16ms/step	-	loss:	0.1348
Epoch 362/500					
128/128	2s	16ms/step	-	loss:	0.1444
Epoch 363/500	26	16ms/stan		10001	0 1450
128/128 ————————————————————————————————————	35	16ms/step	-	1055:	0.1450
128/128	3s	19ms/step	_	loss:	0.1102
Epoch 365/500		, с сор			
128/128	3s	19ms/step	-	loss:	0.1196
Epoch 366/500					
128/128 ————————————————————————————————————	2s	17ms/step	-	loss:	0.1040
Epoch 367/500 128/128 ————————————————————————————————————	26	16ms/step	_	1000	a 1196
Epoch 368/500	23	101113/3 сер		1033.	0.1150
•	3s	16ms/step	_	loss:	0.1949
Epoch 369/500					
	2s	16ms/step	-	loss:	0.1084
Epoch 370/500 128/128 ————————————————————————————————————	2-	22/		1	0 1000
Epoch 371/500	35	23ms/step	-	1088:	0.1099
128/128 ————	2s	17ms/step	_	loss:	4.0592
Epoch 372/500		, ,			
	2s	16ms/step	-	loss:	2.1068
Epoch 373/500	_			,	
	3s	16ms/step	-	loss:	1.1548
Epoch 374/500 128/128 ————————————————————————————————————	20	16ms/step	_	1000	0 1252
120/ 120	23	roms/sceb	-	1022.	0.4232

Epoch 375/500 128/128 —————	26	18ms/step		1000	0 4691
Epoch 376/500	25	Tollis/Step	-	1055.	0.4001
	35	20ms/step	_	loss:	0.3725
Epoch 377/500	,,,	201137 3 6 6 7		1033.	0.3723
•	2s	16ms/step	_	loss:	0.3145
Epoch 378/500					
•	2s	16ms/step	-	loss:	0.3840
Epoch 379/500					
128/128	3s	16ms/step	-	loss:	0.3189
Epoch 380/500					
128/128	2s	16ms/step	-	loss:	0.3424
Epoch 381/500	_			-	
128/128	3s	22ms/step	-	loss:	0.3041
Epoch 382/500	4.	17/		1	0 2460
128/128 ————————————————————————————————————	45	17ms/step	-	1088:	0.2468
128/128	25	16ms/step	_	1055.	a 232a
Epoch 384/500	23	1011137 3 сер		1033.	0.2320
128/128	3s	16ms/step	_	loss:	0.2580
Epoch 385/500		, _ с с с р			
128/128	3s	21ms/step	_	loss:	0.2590
Epoch 386/500					
128/128	2s	17ms/step	-	loss:	0.2514
Epoch 387/500					
128/128	2s	16ms/step	-	loss:	0.2142
Epoch 388/500				_	
128/128	2s	16ms/step	-	loss:	0.1592
Epoch 389/500 128/128 ————————————————————————————————————	26	16ms/ston		10001	0 1000
Epoch 390/500	55	16ms/step	-	1055:	0.1808
128/128	25	16ms/step	_	1055.	0 1741
Epoch 391/500	23	101113/3 СЕР		1033.	0.1/41
•	3s	23ms/step	_	loss:	0.1685
Epoch 392/500		, ,			
128/128	2s	16ms/step	-	loss:	0.1781
Epoch 393/500					
128/128	3s	16ms/step	-	loss:	0.2300
Epoch 394/500				_	
	2s	15ms/step	-	loss:	0.1629
Epoch 395/500	2-	1 Cm = / = + - :-		1	0 1600
	25	16ms/step	-	1022:	0.1608
Epoch 396/500 128/128 ————————————————————————————————————	3.	21ms/step		1000	0 2200
120/120	25	zilis/sceb	-	1022;	0.2380

Epoch 397/500					
	5s	17ms/step	-	loss:	0.1718
Epoch 398/500	20	16ms/ston		10001	0 1610
128/128 ————————————————————————————————————	25	16ms/step	-	1088:	0.1610
•	26	16ms/step	_	1000	a 1371
Epoch 400/500	23	Tollis/ Scep	_	1033.	0.13/1
128/128	25	17ms/step	_	loss:	0.1354
Epoch 401/500		17 m3, 3 ccp		1055.	0.133
128/128	3s	22ms/step	_	loss:	0.1357
Epoch 402/500					
128/128	2s	16ms/step	-	loss:	0.1468
Epoch 403/500					
128/128	3s	16ms/step	-	loss:	0.1472
Epoch 404/500					
128/128	2s	16ms/step	-	loss:	0.1260
Epoch 405/500	2-	16		1	0 1640
128/128 ————————————————————————————————————	25	16ms/step	-	1055:	0.1648
Epoch 406/500 128/128 ————————————————————————————————————	26	18ms/step		1000	0 1260
Epoch 407/500	23	Tollis/ 2 ceb	-	1055.	0.1303
128/128	3s	20ms/step	_	loss:	0.1314
Epoch 408/500		_со, о сер			
128/128 ————	2s	16ms/step	_	loss:	0.1602
Epoch 409/500					
128/128	3s	16ms/step	-	loss:	0.1944
Epoch 410/500					
128/128	2s	16ms/step	-	loss:	0.1332
Epoch 411/500				_	
128/128	2s	16ms/step	-	loss:	0.1283
Epoch 412/500	٦.	24/-+		1	0 1445
128/128 ————————————————————————————————————	35	21ms/step	-	1088:	0.1445
•	55	17ms/step	_	1055.	0 1226
Epoch 414/500	,,,	17 m3/ 3 ccp		1033.	0.1220
•	2s	16ms/step	_	loss:	0.1158
Epoch 415/500		,			
128/128	2s	16ms/step	-	loss:	0.1471
Epoch 416/500					
	3s	20ms/step	-	loss:	0.1440
Epoch 417/500				_	
	3s	21ms/step	-	loss:	0.1354
Epoch 418/500	_	47 ()		,	0 4046
128/128	55	17ms/step	-	Toss:	0.1248

Epoch 419/500					
•	2s	16ms/step	_	loss:	0.1402
Epoch 420/500		·			
-	2s	16ms/step	-	loss:	0.3399
Epoch 421/500					
128/128	3s	22ms/step	-	loss:	0.2733
Epoch 422/500					
128/128	2s	17ms/step	-	loss:	0.1494
Epoch 423/500				_	
128/128	2s	16ms/step	-	loss:	0.1472
Epoch 424/500	2 -	16 / 1			0 4305
128/128 ————————————————————————————————————	35	16ms/step	-	loss:	0.1305
Epoch 425/500 128/128	2 c	16ms/step		1000	a 120a
Epoch 426/500	25	10IIIS/Steb	-	1055.	0.1290
128/128	3¢	20ms/step	_	1055.	a 1299
Epoch 427/500	,,	20113/ 3 CCP		1033.	0.1233
128/128	3s	20ms/step	_	loss:	0.1611
Epoch 428/500		,			
128/128	5s	17ms/step	_	loss:	0.1345
Epoch 429/500		·			
128/128	2s	16ms/step	-	loss:	0.1238
Epoch 430/500					
128/128	3s	20ms/step	-	loss:	0.1462
Epoch 431/500				_	
128/128	3s	23ms/step	-	loss:	0.1333
Epoch 432/500		10 / 1			0 1206
128/128 ————————————————————————————————————	45	18ms/step	-	loss:	0.1396
Epoch 433/500 128/128 ————————————————————————————————————	26	16ms/step	_	1000	a 110 <i>1</i>
Epoch 434/500	23	Tollis/ Scep	_	1033.	0.1194
128/128	35	16ms/step	_	loss:	0.3360
Epoch 435/500		2011137 3 сер		1055.	0.3300
128/128 ————	3s	22ms/step	_	loss:	0.1418
Epoch 436/500		·			
128/128	4s	17ms/step	-	loss:	0.1453
Epoch 437/500					
128/128	2s	16ms/step	-	loss:	0.1131
Epoch 438/500					
	2s	16ms/step	-	loss:	0.1403
Epoch 439/500	2 -	47 / 1		1 -	0 1206
	25	17ms/step	-	Toss:	0.1206
Epoch 440/500	2.	21		1	0 1210
128/128	35	21ms/step	-	TOSS:	0.1310

Epoch 441/500					
	5s	17ms/step	_	loss:	0.1184
Epoch 442/500		·			
•	2s	16ms/step	_	loss:	0.1548
Epoch 443/500		·			
128/128	2s	16ms/step	-	loss:	0.1707
Epoch 444/500					
128/128	3s	23ms/step	-	loss:	0.1600
Epoch 445/500					
128/128	4 s	17ms/step	-	loss:	0.1095
Epoch 446/500					
128/128	2 s	16ms/step	-	loss:	0.1394
Epoch 447/500					
	2s	16ms/step	-	loss:	0.1135
Epoch 448/500					
	3s	21ms/step	-	loss:	0.1101
Epoch 449/500					
128/128	3s	20ms/step	-	loss:	0.1484
Epoch 450/500				_	
128/128	2s	16ms/step	-	loss:	0.1330
Epoch 451/500	_			-	
128/128	3s	16ms/step	-	loss:	0.1461
Epoch 452/500	_			-	
128/128	2s	16ms/step	-	loss:	0.2305
Epoch 453/500	2-	16		1	0 1301
128/128	25	16ms/step	-	1088:	0.1391
Epoch 454/500	2.0	22ms/ston		1000.	0 1751
128/128 ————————————————————————————————————	55	22ms/step	-	1055:	0.1/51
128/128	2 c	18ms/step	_	1000	0 12//
Epoch 456/500	23	тошз/зсер	_	1033.	0.1244
128/128	25	16ms/step	_	1055.	a 1211
Epoch 457/500	23	101113/3сср		1033.	0.1211
128/128	2s	16ms/step	_	loss:	0.1590
Epoch 458/500		,,			
128/128 ————	3s	16ms/step	_	loss:	0.2172
Epoch 459/500		, _F			
128/128	3s	19ms/step	_	loss:	0.1275
Epoch 460/500		·			
	3s	20ms/step	-	loss:	0.1253
Epoch 461/500		·			
128/128	2s	17ms/step	-	loss:	0.1195
Epoch 462/500					
128/128	3s	17ms/step	-	loss:	0.1088

Epoch 463/500					
	25	16ms/step	_	loss:	0.1417
Epoch 464/500		203, 3 сер		1055.	0.1.17
	25	17ms/step	_	loss:	0.8703
Epoch 465/500		_/o, o cep			0.07.00
	3s	22ms/step	_	loss:	0.1584
Epoch 466/500		-,			
•	5s	18ms/step	_	loss:	0.1526
Epoch 467/500		, ,			
128/128	2s	17ms/step	_	loss:	0.1530
Epoch 468/500		·			
128/128	2s	16ms/step	_	loss:	0.1271
Epoch 469/500		·			
128/128	3s	21ms/step	-	loss:	0.1025
Epoch 470/500					
128/128	2s	19ms/step	-	loss:	0.1253
Epoch 471/500					
128/128	2s	16ms/step	-	loss:	0.1050
Epoch 472/500					
	2s	16ms/step	-	loss:	0.1482
Epoch 473/500					
	3s	16ms/step	-	loss:	0.1210
Epoch 474/500					
128/128	2s	17ms/step	-	loss:	0.0988
Epoch 475/500				_	
128/128	3s	22ms/step	-	loss:	0.1233
Epoch 476/500				_	
128/128	4s	17ms/step	-	loss:	0.1012
Epoch 477/500	•	16 / 1			0 4050
128/128	25	16ms/step	-	loss:	0.1258
Epoch 478/500	2 -	16 / 1			0 4300
	35	16ms/step	-	Toss:	0.1388
Epoch 479/500 128/128	2.0	22mc/ston		1000	0 0000
Epoch 480/500	55	zziis/step	-	1055:	0.0889
•	10	17ms/step		1000	0 0002
Epoch 481/500	43	1/1115/3Ceb	-	1055.	0.0332
128/128	26	16ms/stan	_	1000	0 1008
Epoch 482/500	23	тошз/ эсер	_	1033.	0.1000
•	25	16ms/step	_	1055.	0.0916
Epoch 483/500		20113/3ccp		1033.	3.0310
•	3s	19ms/step	_	loss:	0.1448
Epoch 484/500		, эсер			3.2.10
•	3s	21ms/step	_	loss:	0.1263
, 		, эсер			303

Epoch 485/500

```
128/128 -
                                       5s 17ms/step - loss: 0.1077
          Epoch 486/500
          128/128 -
                                        2s 16ms/step - loss: 0.1186
          Epoch 487/500
          128/128 -
                                        2s 16ms/step - loss: 0.1087
          Epoch 488/500
          128/128 -
                                        3s 22ms/step - loss: 0.0982
          Epoch 489/500
          128/128 -
                                        5s 17ms/step - loss: 0.1113
          Epoch 490/500
          128/128 -
                                        2s 17ms/step - loss: 0.1037
          Epoch 491/500
          128/128 -
                                        2s 16ms/step - loss: 1.4874
          Epoch 492/500
          128/128 -
                                        2s 18ms/step - loss: 0.3942
          Epoch 493/500
                                        3s 20ms/step - loss: 0.1447
          128/128 -
          Epoch 494/500
          128/128
                                        2s 16ms/step - loss: 0.1395
          Epoch 495/500
          128/128
                                        3s 16ms/step - loss: 0.1562
          Epoch 496/500
                                        3s 16ms/step - loss: 0.1228
          128/128 -
          Epoch 497/500
          128/128 -
                                        2s 16ms/step - loss: 0.1293
          Epoch 498/500
          128/128 -
                                        3s 23ms/step - loss: 0.1372
          Epoch 499/500
          128/128 -
                                        4s 17ms/step - loss: 0.1470
          Epoch 500/500
          128/128 -
                                       2s 16ms/step - loss: 0.1523
          32/32 -
                                     1s 12ms/step
In [15]: # Split data into training and testing for GDP Per Capita
          X train pc, X test pc, y train pc, y test pc = train test split(X lstm, y gdp per capita, test size=0.2, random state=42)
          # Building the LSTM Model
          model gdp pc = Sequential()
          model gdp pc.add(LSTM(50, return sequences=True, input shape=(X train pc.shape[1], 1)))
          model gdp pc.add(Dropout(0.2))
          model gdp pc.add(LSTM(50, return sequences=False))
          model gdp pc.add(Dropout(0.2))
          model gdp pc.add(Dense(25))
```

```
model_gdp_pc.add(Dense(1))

# Compile the model
model_gdp_pc.compile(optimizer=Adam(learning_rate=0.001), loss='mean_squared_error')

# Train the model
model_gdp_pc.fit(X_train_pc, y_train_pc, batch_size=32, epochs=500)

# Predicting GDP Per Capita
pred_gdp_pc = model_gdp_pc.predict(X_test_pc)
```

Epoch 1/500		
	- 4s 20ms/step - loss: 27.493	17
Epoch 2/500	15 Zomo, Scep 1053. 27. 195	
	- 5s 16ms/step - loss: 2.9432	2
Epoch 3/500		
	- 2s 15ms/step - loss: 2.7936	5
Epoch 4/500		
128/128	- 3s 15ms/step - loss: 2.8612	2
Epoch 5/500		
	- 3s 20ms/step - loss: 2.8953	l
Epoch 6/500		
128/128	- 5s 16ms/step - loss: 2.8118	3
Epoch 7/500	2-45 / 1 2 205	_
128/128	- 2s 15ms/step - loss: 2.8858	3
Epoch 8/500	20 15mg/ston loss 2 967	
128/128 ————————————————————————————————————	- 3s 15ms/step - loss: 2.8678	3
128/128	- 3s 19ms/step - loss: 2.8209	a
Epoch 10/500	33 13113/30ep - 1033. 2.020.	
128/128	- 2s 18ms/step - loss: 2.762!	5
Epoch 11/500	25 105, 5 ccp 1055. 21702.	
128/128	- 2s 15ms/step - loss: 2.7313	3
Epoch 12/500	•	
•	- 2s 15ms/step - loss: 2.8288	3
Epoch 13/500		
128/128	- 2s 15ms/step - loss: 2.7653	1
Epoch 14/500		
	- 3s 15ms/step - loss: 2.8090	Э
Epoch 15/500		_
	- 3s 21ms/step - loss: 2.7918	3
Epoch 16/500	2- 16/	_
	- 2s 16ms/step - loss: 2.7776)
Epoch 17/500 128/128	- 2s 15ms/step - loss: 2.8912)
Epoch 18/500	23 13m3/3cep - 1033. 2:0312	_
•	- 2s 15ms/step - loss: 2.7358	8
Epoch 19/500	25 155, 5 ccp 1053. 21755	
128/128	- 2s 15ms/step - loss: 2.769	7
Epoch 20/500	·	
•	- 3s 16ms/step - loss: 2.7632	2
Epoch 21/500		
	- 3s 20ms/step - loss: 2.7048	3
Epoch 22/500		
128/128	- 5s 16ms/step - loss: 2.8943	3

Epoch 23/500					
128/128	2s	15ms/step	-	loss:	2.6814
Epoch 24/500					
	3s	15ms/step	-	loss:	2.7112
Epoch 25/500	_			_	
	3s	23ms/step	-	loss:	2.7009
Epoch 26/500				-	
128/128 ————————————————————————————————————	45	16ms/step	-	loss:	2./5/9
•	26	15ms/step	_	1000	2 6203
Epoch 28/500	23	13113/3CEP	_	1033.	2.0203
•	35	16ms/step	_	loss:	2.6115
Epoch 29/500	-	203, 3 сер		1055.	2.0113
128/128	3s	22ms/step	_	loss:	2.7116
Epoch 30/500					
	2s	16ms/step	-	loss:	2.6306
Epoch 31/500					
128/128	2s	15ms/step	-	loss:	2.5945
Epoch 32/500					
128/128	2s	15ms/step	-	loss:	2.7535
Epoch 33/500	_	4- / /		-	0 (5.46
128/128	3s	15ms/step	-	loss:	2.6546
Epoch 34/500	2.0	20ms /ston		10001	2 (411
128/128 ————————————————————————————————————	35	20ms/step	-	1088:	2.6411
•	55	17ms/step	_	1055.	2 5880
Epoch 36/500	,,,	17 m3/ 3 ccp		1033.	2.3000
128/128	2s	15ms/step	_	loss:	2.5145
Epoch 37/500		, _F			
128/128	3s	15ms/step	-	loss:	2.5827
Epoch 38/500					
	2s	19ms/step	-	loss:	2.5863
Epoch 39/500					
	2s	18ms/step	-	loss:	2.5400
Epoch 40/500	•	45 / 1			2 5474
	25	15ms/step	-	loss:	2.54/1
Epoch 41/500 128/128 ——————	3 c	15ms/stan	_	1000	2 /1222
Epoch 42/500	23	אס איפווירד (פווירד	-	TO22.	4.4000
•	3s	16ms/step	_	loss:	2,6560
Epoch 43/500	23	_оэ, эсср		1000.	
•	2s	18ms/step	_	loss:	2.5479
Epoch 44/500		'			
•	3s	20ms/step	-	loss:	2.4905
		·			

Epoch 45/500					
128/128	5s	17ms/step	-	loss:	2.4567
Epoch 46/500					
	2s	15ms/step	-	loss:	2.5394
Epoch 47/500				_	
	3s	16ms/step	-	loss:	2.5131
Epoch 48/500	_			-	
128/128	35	21ms/step	-	loss:	2.4896
Epoch 49/500 128/128	20	16ms/step		1000	2 0256
Epoch 50/500	23	Tollis/ 2 ceb	-	1055.	3.0230
128/128	25	15ms/step	_	1055.	2 8009
Epoch 51/500	23	1511137 3 CCP		1033.	2.0003
128/128	2s	15ms/step	_	loss:	2.6400
Epoch 52/500		,			
128/128	2s	15ms/step	_	loss:	2.5567
Epoch 53/500					
128/128	2s	17ms/step	-	loss:	2.4561
Epoch 54/500					
128/128	3s	20ms/step	-	loss:	2.4818
Epoch 55/500	_			_	
128/128	5s	17ms/step	-	loss:	2.4807
Epoch 56/500	•	45 / 1		,	2 4207
128/128 ————————————————————————————————————	25	15ms/step	-	loss:	2.438/
Epoch 57/500 128/128	20	16ms/step		1000	2 5267
Epoch 58/500	23	Tollis/ Scep	_	1033.	2.5507
128/128	35	21ms/step	_	loss:	2.3740
Epoch 59/500	-	223, 3 сер		1055.	2.37 10
128/128	5s	17ms/step	_	loss:	2.5075
Epoch 60/500		·			
128/128	2s	16ms/step	-	loss:	2.4162
Epoch 61/500					
	3s	16ms/step	-	loss:	2.4183
Epoch 62/500				_	
	3s	21ms/step	-	loss:	2.4768
Epoch 63/500	2-	10/		1	2 2000
128/128 ————————————————————————————————————	25	18ms/step	-	1055:	2.3808
Epoch 64/500 128/128 ————————————————————————————————————	26	15ms/step		1000	2 5069
Epoch 65/500	25	אין אין אין אין אין אין אין אין	-	1022:	2.3000
•	35	15ms/step	_	1055.	2.4523
Epoch 66/500		, сер			
•	3s	15ms/step	_	loss:	2.3890

Epoch 67/500					
	2s	17ms/step	-	loss:	2.4420
Epoch 68/500 128/128	2.	20ms/step		1000	2 2262
Epoch 69/500	23	zoilis/step	_	1055.	2.3202
•	2s	16ms/step	_	loss:	2.3340
Epoch 70/500		, _F			
•	3s	15ms/step	-	loss:	2.4323
Epoch 71/500					
128/128	2s	15ms/step	-	loss:	2.3839
Epoch 72/500	_	4- / /		-	0 4400
128/128 ————————————————————————————————————	35	15ms/step	-	loss:	2.4123
Epoch 73/500 128/128 ————————————————————————————————————	3 c	21ms/step	_	1000	2 /121
Epoch 74/500	23	211113/3CEP	_	1033.	2,4121
128/128	2s	15ms/step	_	loss:	2.4154
Epoch 75/500		,			
128/128	3s	16ms/step	-	loss:	2.3716
Epoch 76/500					
128/128	2s	16ms/step	-	loss:	2.4196
Epoch 77/500	•	16 / 1			2 4200
128/128 ————————————————————————————————————	25	16ms/step	-	loss:	2.4288
Epoch 78/500 128/128 ————————————————————————————————————	26	19ms/step	_	1000	2 3606
Epoch 79/500	23	191113/3 СЕР	_	1033.	2.3000
128/128	2s	18ms/step	_	loss:	2.4305
Epoch 80/500					
128/128	2s	16ms/step	-	loss:	2.4108
Epoch 81/500					
128/128	3s	16ms/step	-	loss:	2.4235
Epoch 82/500	2-	16		1	2 4226
128/128 ————————————————————————————————————	25	16ms/step	-	1088:	2.4326
•	35	17ms/step	_	loss:	2.3248
Epoch 84/500		_/o, o cep			_,,,
•	3s	21ms/step	_	loss:	2.4256
Epoch 85/500					
128/128	2s	15ms/step	-	loss:	2.4019
Epoch 86/500	_				
	2s	15ms/step	-	loss:	2.3553
Epoch 87/500 128/128	20	15ms/step	_	1000	2 /210
Epoch 88/500	43	אס / פווורד / ברוור	-	TO22.	∠• + 313
•	25	15ms/step	_	loss:	2,3000
,		, J CCP			

3s	19ms/step	-	loss:	2.4691
2 -	20 / 1			2 2620
35	20ms/step	-	loss:	2.3638
5 c	17ms/stan	_	1000	2 4044
23	1/11/3/3CEP	_	1033.	2.4044
25	15ms/sten	_	loss:	2.4210
	133, 3 сер		1033.	2210
2s	16ms/step	_	loss:	2.4268
3s	21ms/step	-	loss:	2.3425
2s	17ms/step	-	loss:	2.4313
_			_	
2s	16ms/step	-	loss:	2.4381
26	16mc/ston		1000	2 2672
25	10IIIS/Sceb	-	1055.	2.30/2
25	16ms/sten	_	loss:	2.3500
	203, 3 сер		1033.	2.3300
3s	19ms/step	_	loss:	2.4033
3s	19ms/step	-	loss:	2.4213
			_	
2s	16ms/step	-	loss:	2.3339
2 -				
	1 Cmc / c+on		10001	2 4540
35	16ms/step	-	loss:	2.4548
	·			
	16ms/step			
3s	·	-	loss:	2.3422
3s 2s	16ms/step	-	loss:	2.3422
3s 2s	16ms/step	-	loss:	2.3422
3s 2s 3s	16ms/step 16ms/step 21ms/step	-	loss: loss:	2.3422 2.4687 2.3821
3s 2s 3s	16ms/step	-	loss: loss:	2.3422 2.4687 2.3821
3s 2s 3s 5s	16ms/step 16ms/step 21ms/step 16ms/step	-	loss: loss: loss:	2.3422 2.4687 2.3821 2.4294
3s 2s 3s 5s	16ms/step 16ms/step 21ms/step	-	loss: loss: loss:	2.3422 2.4687 2.3821 2.4294
3s 2s 3s 5s 2s	16ms/step 16ms/step 21ms/step 16ms/step 15ms/step		loss: loss: loss: loss:	2.3422 2.4687 2.3821 2.4294 2.3388
3s 2s 3s 5s 2s	16ms/step 16ms/step 21ms/step 16ms/step		loss: loss: loss: loss:	2.3422 2.4687 2.3821 2.4294 2.3388
3s 2s 3s 5s 2s 2s	16ms/step 16ms/step 21ms/step 16ms/step 15ms/step		loss: loss: loss: loss: loss:	2.3422 2.4687 2.3821 2.4294 2.3388 2.2741
3s 2s 3s 5s 2s 2s	16ms/step 16ms/step 21ms/step 16ms/step 15ms/step 16ms/step		loss: loss: loss: loss: loss:	2.3422 2.4687 2.3821 2.4294 2.3388 2.2741
	3s 5s 2s 2s 3s 2s 3s 3s 2s 3s 2s	3s 20ms/step 5s 17ms/step 2s 15ms/step 2s 16ms/step 2s 17ms/step 2s 17ms/step 3s 16ms/step 3s 16ms/step 3s 19ms/step 3s 19ms/step	3s 20ms/step - 5s 17ms/step - 2s 15ms/step - 3s 21ms/step - 2s 17ms/step - 2s 16ms/step - 3s 16ms/step - 3s 16ms/step - 3s 19ms/step - 3s 19ms/step -	<pre>3s 19ms/step - loss: 3s 20ms/step - loss: 5s 17ms/step - loss: 2s 15ms/step - loss: 2s 16ms/step - loss: 2s 17ms/step - loss: 2s 16ms/step - loss: 3s 16ms/step - loss: 3s 16ms/step - loss: 3s 19ms/step - loss:</pre>

Epoch 111/500					
•	2s	16ms/step	_	loss:	2.4131
Epoch 112/500		·			
128/128	3s	16ms/step	-	loss:	2.3639
Epoch 113/500					
128/128	2s	16ms/step	-	loss:	2.4181
Epoch 114/500					
128/128	3s	18ms/step	-	loss:	2.4427
Epoch 115/500	_	22 / 1		-	
128/128	35	20ms/step	-	loss:	2.3449
Epoch 116/500 128/128	20	16ms/ston		10001	2 2022
Epoch 117/500	25	16ms/step	-	1022:	2.3823
128/128	25	16ms/step	_	1055.	2 3682
Epoch 118/500		103, 3 сер		1033.	2.3002
128/128	3s	16ms/step	_	loss:	2.3903
Epoch 119/500		,			
128/128	3s	16ms/step	-	loss:	2.3471
Epoch 120/500					
128/128	3s	20ms/step	-	loss:	2.3618
Epoch 121/500					
128/128	2s	16ms/step	-	loss:	2.3746
Epoch 122/500	_			-	
128/128 ————————————————————————————————————	35	16ms/step	-	loss:	2.3/29
Epoch 123/500 128/128 ————————————————————————————————————	26	16ms/step		1000	2 2050
Epoch 124/500	23	Tollis/ Steb	-	1055.	2.3930
128/128	25	16ms/step	_	loss:	2.3738
Epoch 125/500		1011137 3 сер		1033.	2.3730
128/128	3s	21ms/step	_	loss:	2.3929
Epoch 126/500		·			
128/128	2s	17ms/step	-	loss:	2.4241
Epoch 127/500					
128/128	2s	16ms/step	-	loss:	2.4218
Epoch 128/500	_			-	
	2s	16ms/step	-	loss:	2.4120
Epoch 129/500 128/128 ————————————————————————————————————	20	15mc/ston		10001	2 2064
	25	15ms/sceb	-	1022:	2.3864
Epoch 130/500 128/128	3¢	17ms/step	_	1055.	2 3646
Epoch 131/500	23	-/1113/3cch	-	1033.	2.5040
-	3s	22ms/step	_	loss:	2.4253
Epoch 132/500	_	, F		•	
•	2s	16ms/step	-	loss:	2.3783
		·			

Epoch 133/500					
128/128	3s	16ms/step	_	loss:	2.4140
Epoch 134/500					
128/128	25	16ms/step	_	loss:	2.4235
Epoch 135/500					
128/128	3s	16ms/step	_	loss:	2.3450
Epoch 136/500		, ,			
128/128	3s	20ms/step	_	loss:	2.3977
Epoch 137/500					
128/128	5s	17ms/step	-	loss:	2.3536
Epoch 138/500					
128/128	2s	16ms/step	-	loss:	2.4564
Epoch 139/500					
128/128	3s	16ms/step	-	loss:	2.3863
Epoch 140/500					
128/128	3s	22ms/step	-	loss:	2.2712
Epoch 141/500					
128/128	2s	16ms/step	-	loss:	2.3252
Epoch 142/500					
128/128	3s	16ms/step	-	loss:	2.4414
Epoch 143/500	_			-	
128/128	2s	16ms/step	-	loss:	2.4444
Epoch 144/500	_			-	
128/128	35	16ms/step	-	loss:	2.2995
Epoch 145/500	2-	21		1	2 2055
128/128 ————————————————————————————————————	55	21ms/step	-	1022:	2.3933
Epoch 146/500 128/128	26	17ms/step		1000	2 2004
Epoch 147/500	25	1/11/3/3 cep	-	1055.	2.3994
-	25	16ms/step	_	1055.	2 4263
Epoch 148/500	23	1011137 3 сер		1033.	2.4203
•	35	16ms/step	_	loss:	2.3391
Epoch 149/500					
	2s	16ms/step	_	loss:	2.4054
Epoch 150/500					
-	3s	18ms/step	_	loss:	2.4050
Epoch 151/500		·			
128/128	3s	21ms/step	-	loss:	2.3037
Epoch 152/500					
128/128	2s	16ms/step	-	loss:	2.4304
Epoch 153/500					
128/128	2s	16ms/step	-	loss:	2.3072
Epoch 154/500					
128/128	3s	16ms/step	-	loss:	2.4005

Epoch 155/500	2-	16		1	2 2007
	25	16ms/step	-	1055:	2.3807
Epoch 156/500 128/128 ————————————————————————————————————	3 c	20ms/step	_	1000	2 323/
Epoch 157/500	23	20113/3 CEP		1033.	2.3234
•	5s	17ms/step	_	loss:	2.4123
Epoch 158/500		,			
128/128	2s	16ms/step	_	loss:	2.3988
Epoch 159/500					
128/128	2s	16ms/step	-	loss:	2.3938
Epoch 160/500					
128/128	3s	19ms/step	-	loss:	2.4224
Epoch 161/500	_			_	
128/128	3s	20ms/step	-	loss:	2.4248
Epoch 162/500	•	16 / 1		,	2 2020
128/128 ————————————————————————————————————	25	16ms/step	-	loss:	2.3830
Epoch 163/500 128/128 ————————————————————————————————————	2 c	16ms/step		1000	2 /2/2
Epoch 164/500	23	Tollis/ 2 ceb	-	1055.	2.4343
128/128	35	16ms/step	_	loss	2 4537
Epoch 165/500	,,,	1011137 3 сер		1033.	2.4337
128/128 ————	2s	16ms/step	_	loss:	2.4361
Epoch 166/500					
128/128	3s	22ms/step	-	loss:	2.4346
Epoch 167/500					
128/128	2s	16ms/step	-	loss:	2.3691
Epoch 168/500					
128/128	2s	16ms/step	-	loss:	2.3925
Epoch 169/500	2 -	16 / 1		,	2 2505
128/128	35	16ms/step	-	loss:	2.3585
Epoch 170/500 128/128	26	16ms/step		1000	2 /151
Epoch 171/500	25	10IIIS/Steb	-	1055.	2.4151
128/128	3s	22ms/step	_	loss:	2.4293
Epoch 172/500		, , , , , ,			
•	2s	16ms/step	_	loss:	2.3422
Epoch 173/500		·			
128/128	2s	16ms/step	-	loss:	2.4021
Epoch 174/500					
	2s	16ms/step	-	loss:	2.3187
Epoch 175/500	_			,	
	3s	16ms/step	-	loss:	2.3639
Epoch 176/500	2.	20		1	2 2062
128/128	38	20ms/step	-	TOSS:	2.3862

Epoch 177/500 128/128 —————	56	18ms/step	_	10551	2 3867
Epoch 178/500	23	101113/3 сер	_	1033.	2.3007
•	2s	16ms/step	_	loss:	2,2939
Epoch 179/500		,,			
•	2s	16ms/step	-	loss:	2.3701
Epoch 180/500					
128/128	2s	19ms/step	-	loss:	2.3129
Epoch 181/500					
128/128	3s	21ms/step	-	loss:	2.3695
Epoch 182/500	_	4- / /		-	
128/128 ————————————————————————————————————	25	15ms/step	-	loss:	2.3860
Epoch 183/500 128/128 ————————————————————————————————————	3 c	15ms/step	_	1000	2 2827
Epoch 184/500	23	13113/3 CEP	_	1033.	2.3037
128/128	3s	16ms/step	_	loss:	2.3606
Epoch 185/500		,,			_,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,
128/128	3s	16ms/step	-	loss:	2.4356
Epoch 186/500					
128/128	3s	21ms/step	-	loss:	2.3510
Epoch 187/500				_	
128/128	5s	17ms/step	-	loss:	2.4003
Epoch 188/500	2-	16		1	2 2145
128/128 ————————————————————————————————————	25	16ms/step	-	1088:	2.3145
128/128	35	16ms/step	_	loss:	2.3558
Epoch 190/500		203, 3 ccp		1055.	2.3330
128/128 ————	3s	22ms/step	_	loss:	2.4056
Epoch 191/500		•			
128/128	2s	18ms/step	-	loss:	2.3333
Epoch 192/500					
128/128	2s	16ms/step	-	loss:	2.3054
Epoch 193/500 128/128 ————————————————————————————————————	26	16ms/step		1000	2 2565
Epoch 194/500	23	101115/3 Сер	-	1055.	2.2303
•	3s	16ms/step	_	loss:	2.2907
Epoch 195/500		_oo, o cop			
128/128	2s	18ms/step	-	loss:	2.3493
Epoch 196/500					
	3s	20ms/step	-	loss:	2.2892
Epoch 197/500	_	4= 4.4		,	
	5s	17ms/step	-	loss:	2.3443
Epoch 198/500 128/128 ————————————————————————————————————	2-	16mc/s+s=		1000	2 2649
120/128	25	16ms/step	-	TOSS:	2.2048

Epoch 199/500					
•	2s	16ms/step	_	loss:	2.2156
Epoch 200/500		·			
128/128	3s	21ms/step	-	loss:	2.2800
Epoch 201/500					
128/128	5s	17ms/step	-	loss:	2.3421
Epoch 202/500					
128/128	2s	16ms/step	-	loss:	2.2125
Epoch 203/500				_	
128/128	3s	16ms/step	-	loss:	2.2898
Epoch 204/500	2 -	24 / 1		,	2 2452
128/128 ————————————————————————————————————	35	21ms/step	-	loss:	2.2452
Epoch 205/500 128/128 ————————————————————————————————————	26	19ms/ston		1000	2 2560
Epoch 206/500	25	18ms/step	-	1055.	2.2500
128/128	25	16ms/step	_	1055.	2 2329
Epoch 207/500	23	101113/3 ССР		1033.	2.2323
128/128	2s	16ms/step	_	loss:	2.5391
Epoch 208/500		,			
128/128	2s	16ms/step	_	loss:	2.5184
Epoch 209/500		·			
128/128	2s	16ms/step	-	loss:	2.3717
Epoch 210/500					
128/128	3s	22ms/step	-	loss:	2.3803
Epoch 211/500					
128/128	5s	17ms/step	-	loss:	2.4153
Epoch 212/500	_			-	
128/128 ————————————————————————————————————	25	16ms/step	-	loss:	2.4244
Epoch 213/500 128/128 ————————————————————————————————————	26	16ms/step	_	1000	2 5038
Epoch 214/500	23	Tollis/ 2 ceb	-	1055.	2.3030
128/128	25	19ms/step	_	1055.	2 3387
Epoch 215/500		1311137 3 CCP		1033.	2.3307
128/128 ————	3s	19ms/step	_	loss:	2.4610
Epoch 216/500					
-	2s	16ms/step	-	loss:	2.4797
Epoch 217/500					
128/128	2s	16ms/step	-	loss:	2.3697
Epoch 218/500					
	2s	16ms/step	-	loss:	2.4568
Epoch 219/500	_			-	
	2s	16ms/step	-	loss:	2.4123
Epoch 220/500	_	22 / 1		,	2 2425
128/128	3s	23ms/step	-	Toss:	2.2480

Epoch 221/500	_			_	
128/128	2s	17ms/step	-	loss:	2.2430
Epoch 222/500	•	16 / 1		,	2 2676
128/128 ————————————————————————————————————	25	16ms/step	-	1055:	2.26/6
Epoch 223/500 128/128	2 c	16ms/step		1000	2 227/
Epoch 224/500	23	Tollis/ Scep	_	1033.	2.33/4
128/128	35	16ms/step	_	1055.	2 1194
Epoch 225/500	"	103, 3 сер		1033.	2.117
128/128	3s	20ms/step	_	loss:	1.8975
Epoch 226/500		·			
128/128	2s	18ms/step	-	loss:	1.6704
Epoch 227/500					
128/128	2s	16ms/step	-	loss:	1.5898
Epoch 228/500					
128/128	3s	16ms/step	-	loss:	2.2772
Epoch 229/500	2-	16		1	1 4046
128/128 ————————————————————————————————————	38	16ms/step	-	1088:	1.4846
Epoch 230/500 128/128 ————————————————————————————————————	3 c	21ms/step	_	1000	1 168/
Epoch 231/500	23	211113/3CEP		1033.	1.1004
128/128	2s	19ms/step	_	loss:	1.0416
Epoch 232/500		, ,			
128/128	2s	16ms/step	-	loss:	1.0839
Epoch 233/500					
128/128	2s	16ms/step	-	loss:	1.0811
Epoch 234/500				_	
128/128	2s	16ms/step	-	loss:	1.0832
Epoch 235/500 128/128 ————————————————————————————————————	26	16ms/step		1000	0 0061
Epoch 236/500	23	Tollis/ Scep	_	1033.	0.9901
128/128	3s	22ms/step	_	loss:	0.9256
Epoch 237/500		, с сор			
128/128	2s	16ms/step	-	loss:	0.8960
Epoch 238/500					
128/128	2s	16ms/step	-	loss:	0.9617
Epoch 239/500				_	
	2s	16ms/step	-	loss:	0.9774
Epoch 240/500	2-	16/		1	0.000
128/128 ————————————————————————————————————	25	16ms/step	-	TOSS:	0.9902
	35	18ms/step	_	1055	0.8443
Epoch 242/500	در	10m3/3ccp		1033.	3.0443
	3s	19ms/step	_	loss:	0.8609
-,		, о сор			

Epoch 243/500					
128/128	2s	16ms/step	-	loss:	0.9354
Epoch 244/500					
	3s	16ms/step	-	loss:	0.8529
Epoch 245/500	_			_	
	3s	16ms/step	-	loss:	0.8084
Epoch 246/500	2-	10		1	0.0050
	25	18ms/step	-	loss:	0.9850
Epoch 247/500 128/128 ——————	3 c	21ms/step	_	1000	0 8334
Epoch 248/500	,,,	211113/3сср		1033.	0.0554
•	2s	16ms/step	_	loss:	0.8710
Epoch 249/500		,,			
128/128	3s	16ms/step	_	loss:	0.8544
Epoch 250/500					
128/128	3s	16ms/step	-	loss:	0.7968
Epoch 251/500					
128/128	3s	16ms/step	-	loss:	1.9135
Epoch 252/500	_			-	4 4530
	35	22ms/step	-	loss:	1.15/9
Epoch 253/500 128/128 ————————————————————————————————————	Λc	17ms/step	_	1055.	0 8808
Epoch 254/500	43	171113/3СЕР	_	1033.	0.0090
128/128	2s	16ms/step	_	loss:	0.7769
Epoch 255/500		,,			
128/128	2s	16ms/step	-	loss:	0.6642
Epoch 256/500					
128/128	3s	23ms/step	-	loss:	0.8220
Epoch 257/500	_			-	
128/128	4s	17ms/step	-	loss:	0.6541
Epoch 258/500 128/128 ————————————————————————————————————	20	16ms/step		1000	0 5040
Epoch 259/500	23	Tollis/ Scep	_	1033.	0.3646
•	2s	16ms/step	_	loss:	0.5938
Epoch 260/500		, ,			
•	2s	18ms/step	-	loss:	0.5404
Epoch 261/500					
128/128	3s	22ms/step	-	loss:	0.6255
Epoch 262/500	_	4= 4.4		,	0 =:=:
	45	17ms/step	-	loss:	0.5154
Epoch 263/500 128/128 ————————————————————————————————————	20	16ms/step	_	1000	0 5222
Epoch 264/500	43	Tollis/ 2 ceb	-	1022.	0.3223
•	25	16ms/step	_	1055.	0.6981
	_3	20113/3ccp		1033.	3.0701

Epoch 265/500					
	3s	23ms/step	-	loss:	0.6523
Epoch 266/500					
	4s	17ms/step	-	loss:	0.4854
Epoch 267/500	_			-	
	2s	16ms/step	-	loss:	0.5511
Epoch 268/500	_			-	0 5455
	35	16ms/step	-	loss:	0.515/
Epoch 269/500 128/128 ————————————————————————————————————	2.0	21mc/ston		1000	0 5427
Epoch 270/500	25	21ms/step	-	1055.	0.5427
128/128	26	19ms/step		1000	A 1012
Epoch 271/500	23	19111S/Steb	-	1055.	0.4012
128/128	25	16ms/step	_	1055.	0 4953
Epoch 272/500		201137 3 6 6 7		1055.	0.1555
128/128	2s	16ms/step	_	loss:	0.5080
Epoch 273/500		,,			
128/128	3s	16ms/step	_	loss:	0.4460
Epoch 274/500					
128/128	3s	19ms/step	-	loss:	0.4598
Epoch 275/500					
128/128	3s	22ms/step	-	loss:	0.5118
Epoch 276/500					
128/128	2s	16ms/step	-	loss:	0.5832
Epoch 277/500	_			-	
128/128	25	16ms/step	-	loss:	0.4/82
Epoch 278/500	2-	16/-		1	0 4726
128/128 ————————————————————————————————————	25	16ms/step	-	1088:	0.4/36
128/128	2¢	16ms/step	_	1000	a 1176
Epoch 280/500	23	101113/3 СЕР		1033.	0.4170
128/128	35	20ms/step	_	loss:	0.4458
Epoch 281/500	-	2011137 3 6 6 7		1055.	0.1150
•	5s	18ms/step	_	loss:	0.4027
Epoch 282/500		·			
128/128	2s	16ms/step	-	loss:	0.4838
Epoch 283/500					
128/128	3s	16ms/step	-	loss:	0.4209
Epoch 284/500					
	3s	20ms/step	-	loss:	0.4955
Epoch 285/500	_			-	:
	5s	17ms/step	-	loss:	0.3784
Epoch 286/500	_	46 ()		,	0 4555
128/128	2 s	16ms/step	-	Toss:	0.4654

Epoch 287/500					
	2s	16ms/step	_	loss:	0.5012
Epoch 288/500		, _ с с с р			
	2s	18ms/step	_	loss:	0.4090
Epoch 289/500		, с сер			
	3s	23ms/step	_	loss:	0.3522
Epoch 290/500		, ,			
	4s	17ms/step	_	loss:	0.4240
Epoch 291/500					
	2s	16ms/step	-	loss:	0.4211
Epoch 292/500					
128/128	3s	16ms/step	-	loss:	0.4503
Epoch 293/500		·			
128/128	3s	23ms/step	-	loss:	0.4287
Epoch 294/500					
128/128	2s	16ms/step	-	loss:	0.3457
Epoch 295/500					
128/128	3s	16ms/step	-	loss:	0.3465
Epoch 296/500					
	2s	16ms/step	-	loss:	0.3455
Epoch 297/500					
	2s	16ms/step	-	loss:	0.4617
Epoch 298/500					
128/128	2s	18ms/step	-	loss:	0.3378
Epoch 299/500				_	
128/128	3s	23ms/step	-	loss:	0.3389
Epoch 300/500				_	
128/128	4s	17ms/step	-	loss:	0.4215
Epoch 301/500	_			-	0 2467
128/128	25	16ms/step	-	loss:	0.316/
Epoch 302/500	•	16 / 1		,	0 2040
128/128 ————————————————————————————————————	25	16ms/step	-	loss:	0.3849
Epoch 303/500 128/128 ————————————————————————————————————	2.0	22mc/ston		1000	0 2514
	55	zziis/step	-	1055:	0.3514
Epoch 304/500 128/128 ————————————————————————————————————	26	17ms/step		1000	0 2002
Epoch 305/500	23	1/11/3/3(eb	_	1055.	0.3633
128/128	2 c	16ms/stan	_	1000	a 2987
Epoch 306/500	23	10113/3cep	_	1033.	0.2507
•	25	16ms/step	_	1055.	0.4035
Epoch 307/500		10m3/3ccp		1033.	3.4055
•	3s	16ms/step	_	loss:	0.4264
Epoch 308/500		_сс, ссер			3
•	3s	19ms/step	_	loss:	0.2901
, 		, эсср			3201

Epoch 309/500 128/128	3¢	20ms/step	_	lossi	a 2991
Epoch 310/500	23	20113/3сср		1033.	0.2331
•	5s	17ms/step	_	loss:	0.2638
Epoch 311/500					
	2s	16ms/step	-	loss:	0.2709
Epoch 312/500	_			-	
	2s	17ms/step	-	loss:	0.2311
Epoch 313/500 128/128 ————————————————————————————————————	2 c	21ms/step	_	1000	0 2/12
Epoch 314/500	23	211113/3CEP		1033.	0.2412
•	5s	17ms/step	_	loss:	0.2265
Epoch 315/500		, ,			
128/128	2s	16ms/step	-	loss:	0.2362
Epoch 316/500					
	2s	16ms/step	-	loss:	0.3403
Epoch 317/500	2-	22==/=+==		1	0 2260
128/128 ————————————————————————————————————	35	22ms/step	-	1088:	0.2369
•	25	16ms/step	_	1055.	0 2530
Epoch 319/500		1011137 3 сер		1033.	0.2330
•	3s	16ms/step	_	loss:	0.2213
Epoch 320/500					
	3s	16ms/step	-	loss:	0.2349
Epoch 321/500	_			-	
128/128	3s	16ms/step	-	loss:	0.2646
Epoch 322/500 128/128 ————————————————————————————————————	3 c	21ms/step	_	1000	a 2292
Epoch 323/500	23	ZIIIS/Step	-	1055.	0.2232
128/128	5s	17ms/step	_	loss:	0.2362
Epoch 324/500		·			
128/128	2s	17ms/step	-	loss:	0.2094
Epoch 325/500				_	
128/128	2s	16ms/step	-	loss:	0.2286
Epoch 326/500 128/128 ————————————————————————————————————	20	10mc/c+on		1000	0 2246
Epoch 327/500	25	19ms/step	-	1055.	0.2340
128/128 ————	3s	20ms/step	_	loss:	0.2216
Epoch 328/500		, F			
	5s	18ms/step	-	loss:	0.2207
Epoch 329/500					
	2s	16ms/step	-	loss:	0.1855
Epoch 330/500	2-	17ma/-+-		1	0 2246
128/128	25	17ms/step	-	TOSS:	0.2346

Epoch 331/500					
	3s	23ms/step	-	loss:	0.2263
Epoch 332/500	4.0	17ms/s+on		1000.	0 1000
128/128 ————————————————————————————————————	45	17ms/step	-	1022:	0.1000
-	25	16ms/step	_	loss:	0.2190
Epoch 334/500		203, 3 сер		1055.	0.2230
128/128 ————	2s	16ms/step	_	loss:	0.2000
Epoch 335/500					
128/128	2s	18ms/step	-	loss:	0.1596
Epoch 336/500					
128/128	3s	22ms/step	-	loss:	0.2010
Epoch 337/500				_	
128/128	2s	16ms/step	-	loss:	0.2156
Epoch 338/500	_			-	0 4605
128/128 ————————————————————————————————————	35	16ms/step	-	loss:	0.1685
Epoch 339/500 128/128 ————————————————————————————————————	26	16ms/step		1000	0 1727
Epoch 340/500	23	Tollis/Scep	-	1055.	0.1/2/
128/128	25	16ms/step	_	1055.	a 2a29
Epoch 341/500		103, 3 сер		1033.	0.2023
128/128 ————	3s	20ms/step	_	loss:	0.2076
Epoch 342/500		·			
128/128	3s	20ms/step	-	loss:	0.1800
Epoch 343/500					
128/128	2s	16ms/step	-	loss:	0.1947
Epoch 344/500					
128/128	3s	16ms/step	-	loss:	0.1892
Epoch 345/500	2-	16		1	0 1467
128/128 ————————————————————————————————————	35	16ms/step	-	TOSS:	0.1467
Epoch 346/500 128/128	26	17ms/step	_	1000	a 1701
Epoch 347/500	23	1/1113/3CEP	_	1033.	0.1/91
128/128	3s	21ms/step	_	loss:	0.1525
Epoch 348/500		-,			
-	5s	17ms/step	_	loss:	0.1726
Epoch 349/500					
128/128	2s	16ms/step	-	loss:	0.2226
Epoch 350/500					
	2s	17ms/step	-	loss:	0.1592
Epoch 351/500	٦-	22 / /		1 -	0 1706
	38	23ms/step	-	TOSS:	0.1/86
Epoch 352/500 128/128	20	17mc/c+05		1000	0 1560
120/128	25	17ms/step	-	TOSS:	Ø.1569

Epoch 353/500	_				
	2s	16ms/step	-	loss:	0.2058
Epoch 354/500	2-	17/		1	0 1642
	35	17ms/step	-	1055:	0.1642
Epoch 355/500 128/128 ————————————————————————————————————	3 c	17ms/step	_	1000	0 1052
Epoch 356/500	23	1/11/3/3(eb	-	1055.	0.1932
•	3¢	22ms/step	_	1055.	0 1442
Epoch 357/500	,,,	221137 3 6 6 7		1033.	0.1442
•	2s	17ms/step	_	loss:	0.1553
Epoch 358/500					
128/128	2s	16ms/step	-	loss:	0.1782
Epoch 359/500					
128/128	3s	16ms/step	-	loss:	0.1568
Epoch 360/500					
128/128	2s	16ms/step	-	loss:	0.1363
Epoch 361/500	_	10 / 1		-	0 4560
128/128	35	19ms/step	-	loss:	0.1560
Epoch 362/500	26	21 ms /s+on		10001	0 1/25
128/128 ————————————————————————————————————	38	21ms/step	-	1088:	0.1435
128/128	25	16ms/step	_	1055.	0 1378
Epoch 364/500		1011137 3 сер		1033.	0.1370
128/128	3s	16ms/step	_	loss:	0.1286
Epoch 365/500		, , , , , ,			
128/128	3s	16ms/step	-	loss:	0.1481
Epoch 366/500					
128/128	4s	35ms/step	-	loss:	0.1504
Epoch 367/500					
128/128	3s	26ms/step	-	loss:	0.1813
Epoch 368/500	_			-	
128/128 ————————————————————————————————————	4s	17ms/step	-	loss:	0.1908
Epoch 369/500 128/128 ————————————————————————————————————	26	17ms/step		1000	0 6201
Epoch 370/500	23	1/11/3/3(eb	-	1055.	0.0201
•	35	17ms/step	_	1055.	0 1678
Epoch 371/500	,,,	1711137 3 6 6 5		1033.	0.1070
128/128	3s	22ms/step	_	loss:	0.2096
Epoch 372/500					
	5s	17ms/step	-	loss:	0.1359
Epoch 373/500					
	2s	16ms/step	-	loss:	0.1469
Epoch 374/500					
128/128	2s	16ms/step	-	loss:	0.2175

Epoch 375/500					
	3s	21ms/step	-	loss:	0.1705
Epoch 376/500					
	5s	17ms/step	-	loss:	0.1774
Epoch 377/500	_			-	
	2s	16ms/step	-	loss:	0.1447
Epoch 378/500	2-	16		1	0 1430
	25	16ms/step	-	1055:	0.1430
Epoch 379/500 128/128 ————————————————————————————————————	26	19ms/step		1000	0 2562
Epoch 380/500	23	191113/3CEP	_	1033.	0.2303
128/128	3¢	21ms/step	_	1055.	0 2197
Epoch 381/500	23	211113/3 СЕР		1033.	0.2137
128/128	2s	17ms/step	_	loss:	0.1558
Epoch 382/500		, с сер			
128/128 ————	3s	24ms/step	_	loss:	0.1411
Epoch 383/500					
128/128	3s	24ms/step	-	loss:	0.1383
Epoch 384/500					
128/128	5s	21ms/step	-	loss:	0.1511
Epoch 385/500					
128/128	2s	16ms/step	-	loss:	0.1703
Epoch 386/500					
128/128	2s	16ms/step	-	loss:	0.1529
Epoch 387/500	_			-	0 4450
128/128	35	16ms/step	-	loss:	0.1459
Epoch 388/500 128/128 ————————————————————————————————————	2-	17/		1	0.0054
Epoch 389/500	25	17ms/step	-	1088:	0.0954
128/128	3 c	22ms/step	_	1000	0 1/66
Epoch 390/500	23	221113/3CEP		1033.	0.1400
128/128	25	18ms/step	_	loss:	0.1821
Epoch 391/500		203, 3 сер		1055.	0.1011
128/128 ————	2s	18ms/step	_	loss:	0.1679
Epoch 392/500		·			
128/128	2s	18ms/step	-	loss:	0.1635
Epoch 393/500					
128/128	2s	16ms/step	-	loss:	0.1209
Epoch 394/500					
	3s	20ms/step	-	loss:	0.1289
Epoch 395/500				_	
	5s	17ms/step	-	loss:	0.1239
Epoch 396/500	_	46 ()		,	0 4405
128/128	2s	16ms/step	-	loss:	0.1183

Epoch 397/500		
	- 2s 17ms/step - loss: 0.1080	
Epoch 398/500		
	2s 17ms/step - loss: 0.1174	
Epoch 399/500		
	3s 21ms/step - loss: 0.1837	
Epoch 400/500	. '	
•	- 2s 16ms/step - loss: 0.1330	
Epoch 401/500	•	
•	2s 16ms/step - loss: 0.1363	
Epoch 402/500		
128/128	3s 16ms/step - loss: 0.1353	
Epoch 403/500		
128/128	• 2s 16ms/step - loss: 0.1454	
Epoch 404/500		
128/128	3s 23ms/step - loss: 0.1554	
Epoch 405/500		
	• 4s 17ms/step - loss: 0.1020	
Epoch 406/500		
	• 2s 16ms/step - loss: 0.1551	
Epoch 407/500		
	• 2s 16ms/step - loss: 0.1073	
Epoch 408/500		
128/128	• 3s 22ms/step - loss: 0.1209	
Epoch 409/500	/	
128/128	- 3s 20ms/step - loss: 0.1684	
Epoch 410/500	2-16 / 1 2 0 1652	
128/128	• 2s 16ms/step - loss: 0.1653	
Epoch 411/500 128/128 ————————————————————————————————————	2c 16ms/ston loss: 0 1025	
	2s 16ms/step - loss: 0.1025	
Epoch 412/500 128/128 ————————————————————————————————————	• 3s 17ms/step - loss: 0.1211	
Epoch 413/500	33 1/11/3/3(ep - 1033. 0.1211	
•	- 3s 18ms/step - loss: 0.1208	
Epoch 414/500	33 103, 3 ccp 1033. 0.1200	
•	- 3s 24ms/step - loss: 0.1582	
Epoch 415/500	23 2 ms, seep 1033. 0.1302	
128/128	4s 18ms/step - loss: 0.0987	
Epoch 416/500	, ,	
•	2s 16ms/step - loss: 0.1611	
Epoch 417/500	•	
•	2s 16ms/step - loss: 0.0980	
Epoch 418/500	•	
	- 3s 20ms/step - loss: 0.1205	

Epoch 419/500					
	5s	17ms/step	-	loss:	0.1005
Epoch 420/500	•	16 / 1		,	0 4400
128/128 ————————————————————————————————————	25	16ms/step	-	loss:	0.1108
Epoch 421/500	2.0	16ms/ston		10001	0 1240
128/128 ————————————————————————————————————	22	16ms/step	-	1055:	0.1240
Epoch 422/500 128/128	2.	20ms/step		1000	0 1064
Epoch 423/500	23	Zollis/step	-	1055.	0.1004
•	5s	17ms/step	_	loss:	0.0989
Epoch 424/500		, с сер			
•	2s	16ms/step	_	loss:	0.1265
Epoch 425/500		, ,			
128/128	3s	16ms/step	-	loss:	0.1117
Epoch 426/500					
128/128	3s	19ms/step	-	loss:	0.1238
Epoch 427/500					
128/128	3s	21ms/step	-	loss:	0.1101
Epoch 428/500					
128/128	5s	18ms/step	-	loss:	0.1042
Epoch 429/500	•	16 / 1		,	0 1000
128/128	25	16ms/step	-	loss:	0.1099
Epoch 430/500 128/128	20	17ms/ston		10001	0 1274
Epoch 431/500	25	17ms/step	-	1055:	0.12/4
128/128	3¢	23ms/step	_	1055.	0 0931
Epoch 432/500	,,	2511137 3 CCP		1033.	0.0551
128/128	2s	16ms/step	_	loss:	0.1502
Epoch 433/500		,,			
128/128	3s	16ms/step	_	loss:	0.0929
Epoch 434/500					
128/128	3s	17ms/step	-	loss:	0.1772
Epoch 435/500					
128/128	2s	17ms/step	-	loss:	0.1003
Epoch 436/500				_	
128/128	3s	24ms/step	-	loss:	0.1448
Epoch 437/500	2-	16		1	0 0011
	25	16ms/step	-	loss:	0.0811
Epoch 438/500	3.	16ms/step		1000	0 0764
128/128 ————————————————————————————————————	22	roms/sceb	-	1022:	0.0/04
•	25	16ms/step	_	1055.	0.1062
Epoch 440/500		10m3/3ccp		1033.	3.1002
•	3s	16ms/step	_	loss:	0.0783
,		_сэ, э сер		_000.	0.07.03

Epoch 441/500					
	3s	22ms/step	_	loss:	0.3835
Epoch 442/500		-,			
128/128	2s	17ms/step	_	loss:	0.0916
Epoch 443/500		-,			
	2s	16ms/step	_	loss:	0.0886
Epoch 444/500		·			
•	3s	16ms/step	-	loss:	0.0871
Epoch 445/500		·			
128/128	2s	16ms/step	-	loss:	0.1147
Epoch 446/500					
128/128	2s	18ms/step	-	loss:	0.0996
Epoch 447/500					
128/128	3s	21ms/step	-	loss:	0.1055
Epoch 448/500					
128/128	2s	17ms/step	-	loss:	0.1009
Epoch 449/500					
128/128	2s	17ms/step	-	loss:	0.1058
Epoch 450/500					
128/128	3s	16ms/step	-	loss:	0.1159
Epoch 451/500					
128/128	2s	16ms/step	-	loss:	0.0843
Epoch 452/500					
128/128	3s	23ms/step	-	loss:	0.0862
Epoch 453/500				_	
128/128	2s	18ms/step	-	loss:	0.0860
Epoch 454/500				_	
128/128	2s	17ms/step	-	loss:	0.1266
Epoch 455/500	_	47 / 1		-	
128/128	25	1/ms/step	-	loss:	0.1285
Epoch 456/500	•	47 / 1		,	0 1061
128/128	25	1/ms/step	-	loss:	0.1064
Epoch 457/500 128/128	20	10mc/ston		1000	A 127E
	25	18ms/steb	-	1055:	0.13/3
Epoch 458/500 128/128	2.0	23ms/step		1000	0 1756
Epoch 459/500	25	23111S/Step	-	1055.	0.1/56
128/128	26	16ms/stan	_	1000	a a782
Epoch 460/500	23	101113/3CEP	_	1033.	0.0/02
•	3 c	17ms/step	_	1055.	0 0797
Epoch 461/500	,,	1/113/3cep	-	1033.	3.0/5/
•	25	17ms/step	_	1055.	0.0835
Epoch 462/500	_3	_,, 5 ccp		1000.	3.0055
•	25	17ms/step	_	1055.	0.0979
,		_/J/ 3 ccp		1033.	3.03/3

Epoch 463/500					
	3s	21ms/step	_	loss:	0.0734
Epoch 464/500		, с сер			
128/128	3s	19ms/step	_	loss:	0.0781
Epoch 465/500		-,			
	2s	16ms/step	_	loss:	0.1427
Epoch 466/500		·			
	3s	16ms/step	_	loss:	0.0663
Epoch 467/500		·			
128/128	3s	16ms/step	-	loss:	0.0688
Epoch 468/500					
128/128	2s	18ms/step	-	loss:	0.0697
Epoch 469/500					
128/128	3s	21ms/step	-	loss:	0.0893
Epoch 470/500					
128/128	2 s	16ms/step	-	loss:	0.1253
Epoch 471/500					
128/128	2s	17ms/step	-	loss:	0.0640
Epoch 472/500					
	2 s	17ms/step	-	loss:	0.0704
Epoch 473/500					
128/128	2s	17ms/step	-	loss:	0.0970
Epoch 474/500					
128/128	3s	23ms/step	-	loss:	0.0885
Epoch 475/500				_	
128/128	4s	18ms/step	-	loss:	0.0969
Epoch 476/500	_			_	
128/128	2s	16ms/step	-	loss:	0.0798
Epoch 477/500	2-	17/-+		1	0 0750
128/128	25	1/ms/step	-	1055:	0.0/59
Epoch 478/500	2-	10/		1	0 0054
128/128 ————————————————————————————————————	35	19ms/step	-	1088:	0.0854
Epoch 479/500 128/128	2 c	20ms/ston		1000	0 0000
Epoch 480/500	23	Zollis/step	-	1055.	0.0003
	26	17ms/step	_	1000	0 0071
Epoch 481/500	23	1/11/3/3 CEP	_	1033.	0.03/1
128/128	25	17ms/sten	_	1055.	0 0863
Epoch 482/500	_3	_,, J ccp		1000.	3.0003
•	25	16ms/step	_	loss:	0.0683
Epoch 483/500		_сс, ссер			3.0003
•	2s	17ms/step	_	loss:	0.2538
Epoch 484/500		-, P		•	
•	3s	23ms/step	_	loss:	0.1124
-	_	F		•	

```
Epoch 485/500
128/128 -
                              2s 18ms/step - loss: 0.0751
Epoch 486/500
128/128 -
                              2s 16ms/step - loss: 0.0595
Epoch 487/500
                              3s 16ms/step - loss: 0.0697
128/128 -
Epoch 488/500
128/128 -
                              2s 17ms/step - loss: 0.1072
Epoch 489/500
                              3s 20ms/step - loss: 0.2016
128/128 -
Epoch 490/500
128/128 -
                              3s 20ms/step - loss: 0.0797
Epoch 491/500
128/128 -
                              5s 17ms/step - loss: 0.0645
Epoch 492/500
128/128 -
                              2s 17ms/step - loss: 0.0688
Epoch 493/500
128/128 -
                              2s 17ms/step - loss: 0.0661
Epoch 494/500
128/128
                              3s 22ms/step - loss: 0.1054
Epoch 495/500
128/128 -
                              2s 17ms/step - loss: 0.0818
Epoch 496/500
                              2s 17ms/step - loss: 0.1201
128/128 -
Epoch 497/500
128/128 -
                              3s 17ms/step - loss: 0.0616
Epoch 498/500
128/128 -
                              2s 17ms/step - loss: 0.0655
Epoch 499/500
128/128 -
                              3s 24ms/step - loss: 0.0594
Epoch 500/500
128/128 -
                              4s 18ms/step - loss: 0.0910
32/32 -
                           1s 13ms/step
```

```
In [16]: from sklearn.metrics import mean_squared_error, r2_score

# Evaluating GDP Model

mse_gdp = mean_squared_error(y_test, pred_gdp)

r2_gdp = r2_score(y_test, pred_gdp)

print(f"GDP Model - MSE: {mse_gdp}, R2: {r2_gdp}")

# Evaluating GDP Per Capita Model

mse_gdp_pc = mean_squared_error(y_test_pc, pred_gdp_pc)
```

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```
r2_gdp_pc = r2_score(y_test_pc, pred_gdp_pc)
print(f"GDP Per Capita Model - MSE: {mse_gdp_pc}, R2: {r2_gdp_pc}")

GDP Model - MSE: 0.04693979024887085, R2: 0.9914343995142781
GDP Per Capita Model - MSE: 0.030671848354972584, R2: 0.9873810983418025
```

These results indicate the performance of Long Short-Term Memory (LSTM) model for two different GDP-related predictions.

1. GDP Model:

- Mean Squared Error (MSE): 0.0469
- R-squared (R²): 0.9914

The MSE of 0.0469 is relatively low, suggesting that the model's predictions are close to the actual values, with minimal error. An R² value of 0.9914 is very high, indicating that approximately 99.14% of the variance in GDP can be explained by the model. This means your model has a strong fit to the GDP data.

2. GDP Per Capita Model:

- Mean Squared Error (MSE): 0.0307
- R-squared (R²): 0.9874

Similarly, the MSE of 0.0307 is low, showing that the model is making accurate predictions with minimal error. The R² value of 0.9874 is also very high, meaning that about 98.74% of the variance in GDP per capita is explained by the model. This indicates a strong fit to the GDP per capita data as well.

Summary:

- Both models exhibit excellent performance, with very high R² values indicating that they are well-suited to predict GDP and GDP per capita.
- The low MSE values for both models show that the predictions are close to the actual values, confirming the models' accuracy and reliability.

```
import matplotlib.pyplot as plt

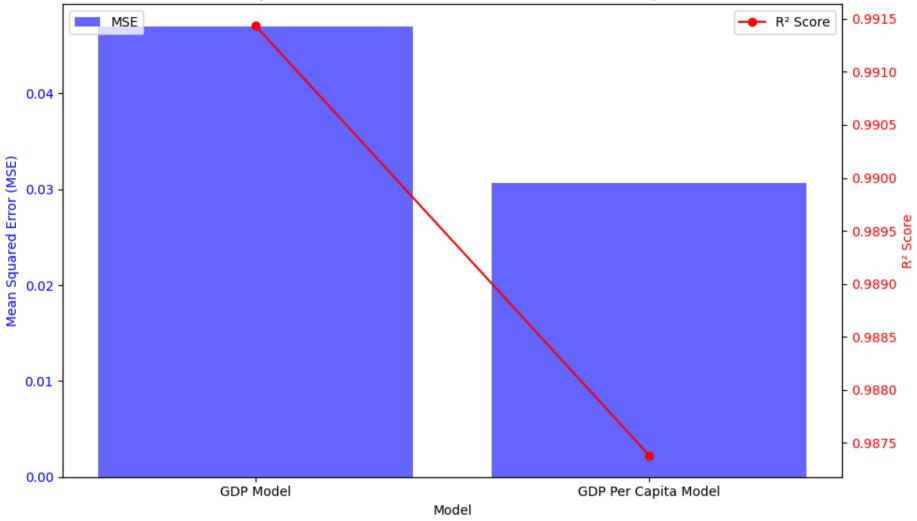
# Define the metrics for each model
models = ['GDP Model', 'GDP Per Capita Model']
mse_values = [mse_gdp, mse_gdp_pc]
r2_values = [r2_gdp, r2_gdp_pc]

# Create a figure and axis
fig, ax1 = plt.subplots(figsize=(10, 6))
```

```
# Plot MSE
ax1.bar(models, mse values, color='blue', alpha=0.6, label='MSE')
ax1.set xlabel('Model')
ax1.set ylabel('Mean Squared Error (MSE)', color='blue')
ax1.tick params(axis='y', labelcolor='blue')
# Create a second y-axis to plot R<sup>2</sup> scores
ax2 = ax1.twinx()
ax2.plot(models, r2_values, color='red', marker='o', label='R2 Score')
ax2.set ylabel('R2 Score', color='red')
ax2.tick params(axis='y', labelcolor='red')
# Add titles and labels
plt.title('Comparison of Model Performance: GDP vs GDP Per Capita')
fig.tight_layout()
# Add Legends
ax1.legend(loc='upper left')
ax2.legend(loc='upper right')
# Show the plot
plt.show()
```

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Comparison of Model Performance: GDP vs GDP Per Capita



The graph presents a comparative analysis of two models—one based on GDP and the other on GDP Per Capita. The performance metrics shown are Mean Squared Error (MSE) and R^2 Score.

Interpretation:

1. MSE (Mean Squared Error):

- Represented by the blue bars on the left y-axis.
- The GDP Model has a higher MSE than the GDP Per Capita Model, indicating that the GDP Model has higher errors in its predictions.
- The lower MSE in the GDP Per Capita Model suggests it is more accurate in predicting the target variable.

2. R² Score:

- Represented by the red line on the right y-axis.
- The GDP Model has a slightly higher R² score than the GDP Per Capita Model, indicating that it explains slightly more variance in the data.
- The downward trend in the R² score from the GDP Model to the GDP Per Capita Model suggests that while the GDP Per Capita Model has lower errors (better MSE), it slightly sacrifices the explained variance.

Conclusion:

• Trade-off Between MSE and R²: The plot indicates a trade-off where the GDP Per Capita Model reduces prediction errors (lower MSE) at the cost of a small decrease in the proportion of variance explained (lower R² score). This suggests that depending on the application, one might prefer the GDP Per Capita Model for its accuracy or the GDP Model for its explanatory power.

This visual helps in understanding which model might be more suitable depending on the specific goals of the analysis, whether it's minimizing error or maximizing the explained variance.