ENSIAS

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Forecasting Demand for Moroccan Local Products in National and International Markets

A Data-Driven Approach

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Introduction

In today's fast-paced market, understanding and meeting consumer demand is crucial, especially for local product industries. Our project, uses data-driven techniques to predict demand patterns. We analyze historical export data and employ predictive models to forecast trends and identify strategic opportunities. This presentation will cover our approach, findings, and their potential impact on the industry.

02

Project Concept

Objectives

Forecasting demand and identifying market trends for Moroccan local products.

Developing data-driven strategies for product development & commercialization.

Cleaning data and selecting relevant products and characteristics for analysis.

Justifying algorithm choices and presenting insights through data visualization

Approach and methodology

1. Data Collection & Exploration
2. Data Visualization
3. Data Cleaning
4. Model Selection & Evaluation
5. Interpretation & Presentation

03

Dataset

Data description

The first few rows of the dataset to visualize the export values by product.

	Code	Product label	Exported value in 2003	Exported value in 2004	Exported value in 2005	Exported value in 2006	Exported value in 2007	Exported value in 2008	Exported value in 2009	Exported value in 2010	...	Exported value in 2013	Exported value in 2014	Exported value in 2015	Exported value in 2016	Exported value in 2017	Exported value in 2018	Exported value in 2019	Exported value in 2020	Exported value in 2021	Exported value in 2022
0	TOTAL	All products	8738341	9870179	11197413	12731303	15321255	20094617	14027369	17764791	...	21967951	23815816	22197567	22850021	25619900	29317739	29592492	27704922	36578743	42331463
1	31	Fertilisers	371608	431325	444344	533674	876747	1412452	697642	1561945	...	1924549	2060879	1872511	2133011	2580227	3168304	2914949	3385504	5714861	7715003
2	87	Vehicles other than railway or tramway rolling...	46680	55256	76111	117890	161777	201129	223629	245346	...	1642522	2456599	2644755	3137905	3394836	3875243	3830883	3614653	5041423	6370692
3	85	Electrical machinery and equipment and parts t...	1176179	1257912	1599657	1930282	2359746	2504401	1998575	2632491	...	3170166	3781969	3509440	3739194	4228090	4925873	5300422	4658452	5249193	5995016
4	62	Articles of apparel and clothing accessories, ...	1952757	2116194	2040800	2377490	2532616	2483422	2236326	2142622	...	2261995	2401451	2060468	2238045	2401926	2533095	2424111	1911834	2518580	2726952

5 rows × 22 columns

Data description

The 5 first rows of the dataset to visualize the growth in export values by product.

	Code	Product label	exportations growth in value between 2003-2004, %	exportations growth in value between 2004-2005, %	exportations growth in value between 2005-2006, %	exportations growth in value between 2006-2007, %	exportations growth in value between 2007-2008, %	exportations growth in value between 2008-2009, %	exportations growth in value between 2009-2010, %	exportations growth in value between 2010-2011, %	...	exportations growth in value between 2013-2014, %	exportations growth in value between 2014-2015, %	exportations growth in value between 2015-2016, %	exportations growth in value between 2016-2017, %	exportations growth in value between 2017-2018, %	exportations growth in value between 2018-2019, %	exportations growth in value between 2019-2020, %	exportations growth in value between 2020-2021, %	exportations growth in value between 2021-2022, %	Exported value in 2022,US Dollar thousand
0	TOTAL	All products	13.0	13.0	14.0	20.0	31.0	-30.0	27.0	22.0	...	8.0	-7.0	3.0	12.0	14.0	1.0	-6.0	32.0	16.0	42331463
1	31	Fertilisers	16.0	3.0	20.0	64.0	61.0	-51.0	124.0	48.0	...	7.0	-9.0	14.0	21.0	23.0	-8.0	16.0	69.0	35.0	7715003
2	87	Vehicles other than railway or tramway rolling...	18.0	38.0	55.0	37.0	24.0	11.0	10.0	74.0	...	50.0	8.0	19.0	8.0	14.0	-1.0	-6.0	39.0	26.0	6370692
3	85	Electrical machinery and equipment and parts t...	7.0	27.0	21.0	22.0	6.0	-20.0	32.0	21.0	...	19.0	-7.0	7.0	13.0	17.0	8.0	-12.0	13.0	14.0	5995016
4	62	Articles of apparel and clothing accessories, ...	8.0	-4.0	16.0	7.0	-2.0	-10.0	-4.0	6.0	...	6.0	-14.0	9.0	7.0	5.0	-4.0	-21.0	32.0	8.0	2726952

5 rows × 22 columns

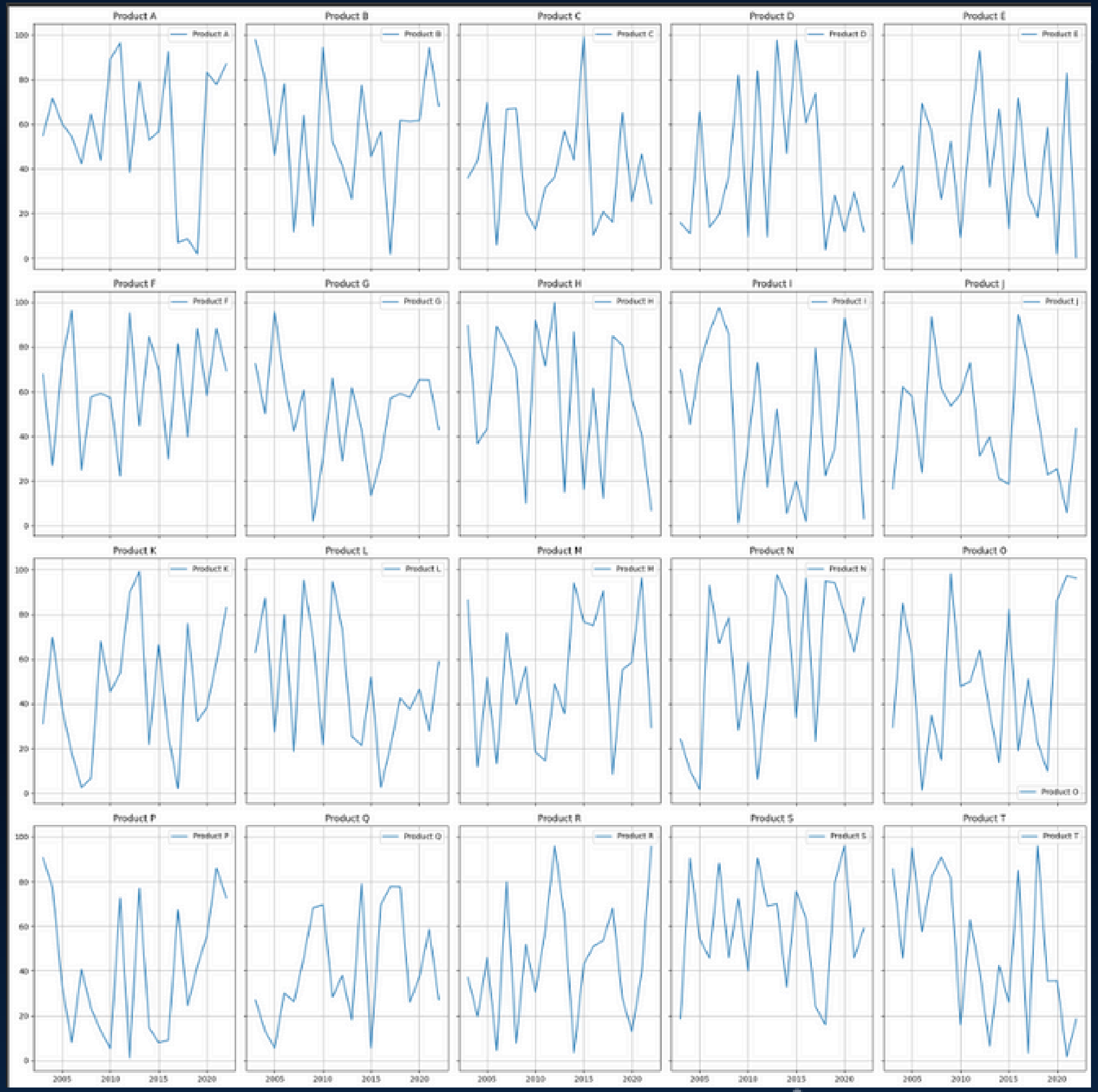
Data description

The 5 first rows of the dataset to visualize the share in export values by product.

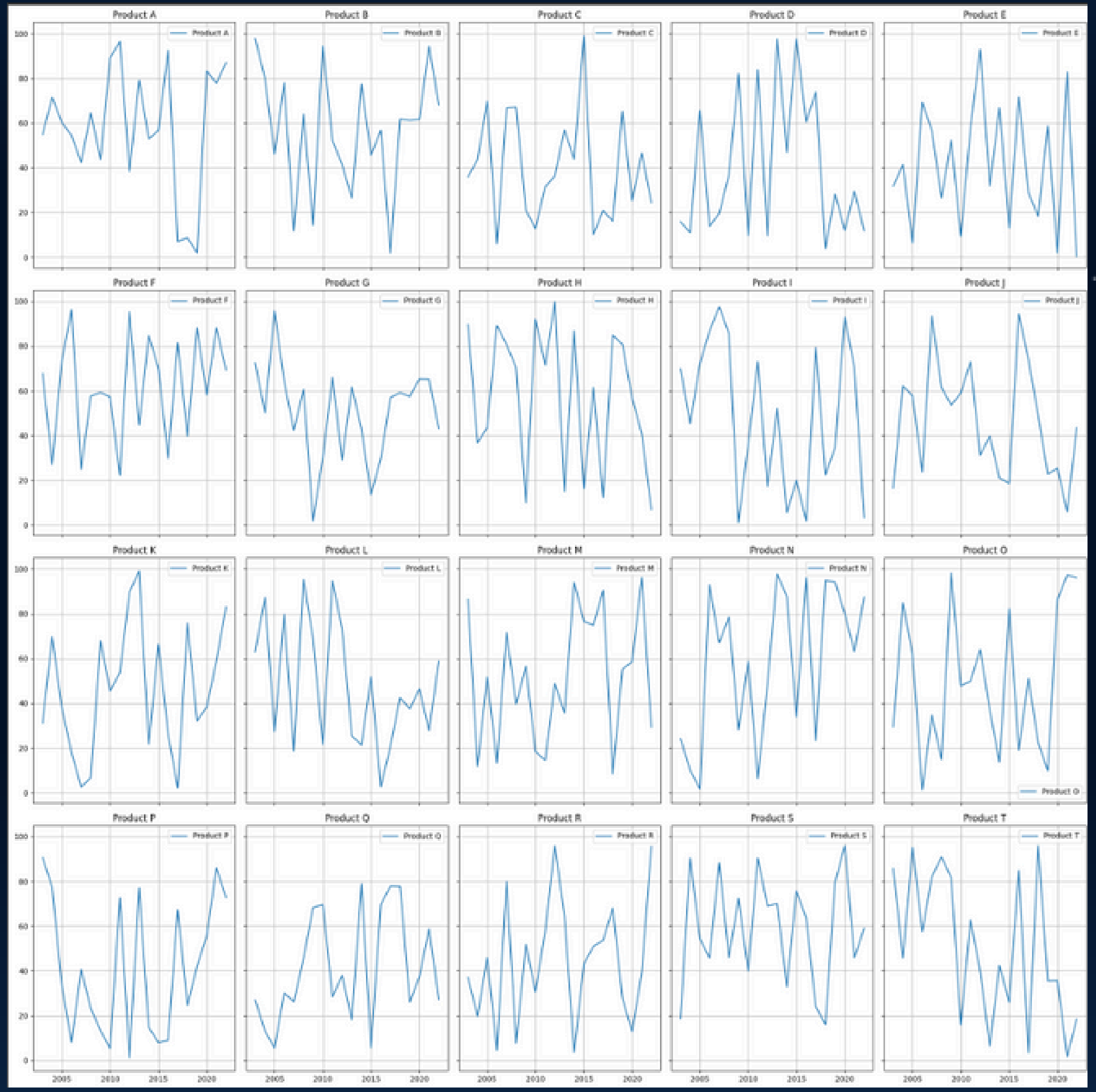
	Code	Product label	Share in value in country's cluster exports, % in 2003	Share in value in country's cluster exports, % in 2004	Share in value in country's cluster exports, % in 2005	Share in value in country's cluster exports, % in 2006	Share in value in country's cluster exports, % in 2007	Share in value in country's cluster exports, % in 2008	Share in value in country's cluster exports, % in 2009	Share in value in country's cluster exports, % in 2010	...	Share in value in country's cluster exports, % in 2013	Share in value in country's cluster exports, % in 2014	Share in value in country's cluster exports, % in 2015	Share in value in country's cluster exports, % in 2016	Share in value in country's cluster exports, % in 2017	Share in value in country's cluster exports, % in 2018	Share in value in country's cluster exports, % in 2019	Share in value in country's cluster exports, % in 2020	Share in value in country's cluster exports, % in 2021	Share in value in country's cluster exports, % in 2022
0	TOTAL	All products	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	...	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
1	31	Fertilisers	4.25	4.37	3.97	4.19	5.72	7.03	4.97	8.79	...	8.76	8.65	8.44	9.33	10.07	10.81	9.85	12.22	15.62	18.23
2	87	Vehicles other than railway or tramway rolling...	0.53	0.56	0.68	0.93	1.06	1.00	1.59	1.38	...	7.48	10.31	11.91	13.73	13.25	13.22	12.95	13.05	13.78	15.05
3	85	Electrical machinery and equipment and parts t...	13.46	12.74	14.29	15.16	15.40	12.46	14.25	14.82	...	14.43	15.88	15.81	16.36	16.50	16.80	17.91	16.81	14.35	14.16
4	62	Articles of apparel and clothing accessories, ...	22.35	21.44	18.23	18.67	16.53	12.36	15.94	12.06	...	10.30	10.08	9.28	9.79	9.38	8.64	8.19	6.90	6.89	6.44

5 rows × 22 columns

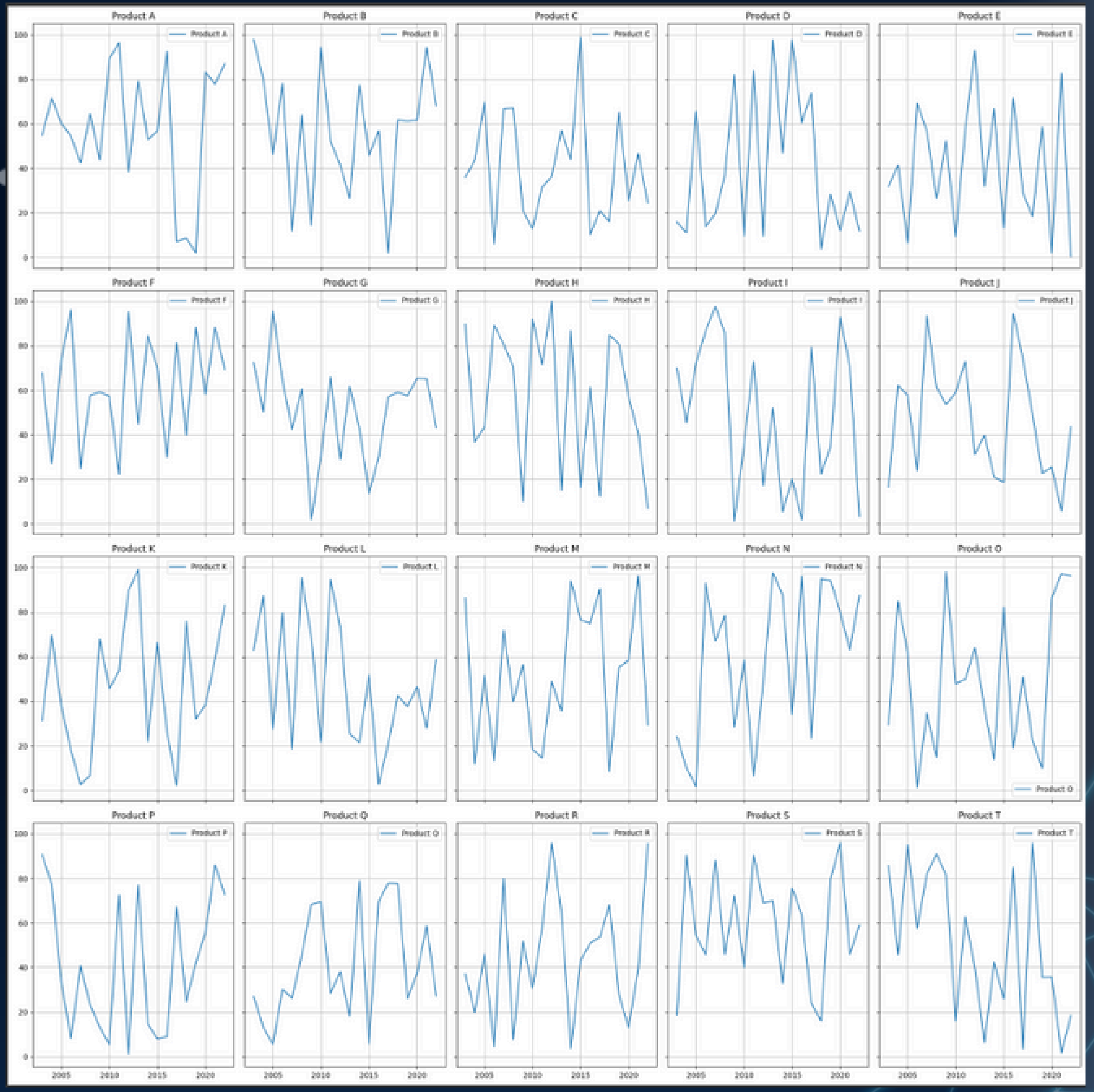
Data visualisation



Displays initial rows to visualize export value growth by product.

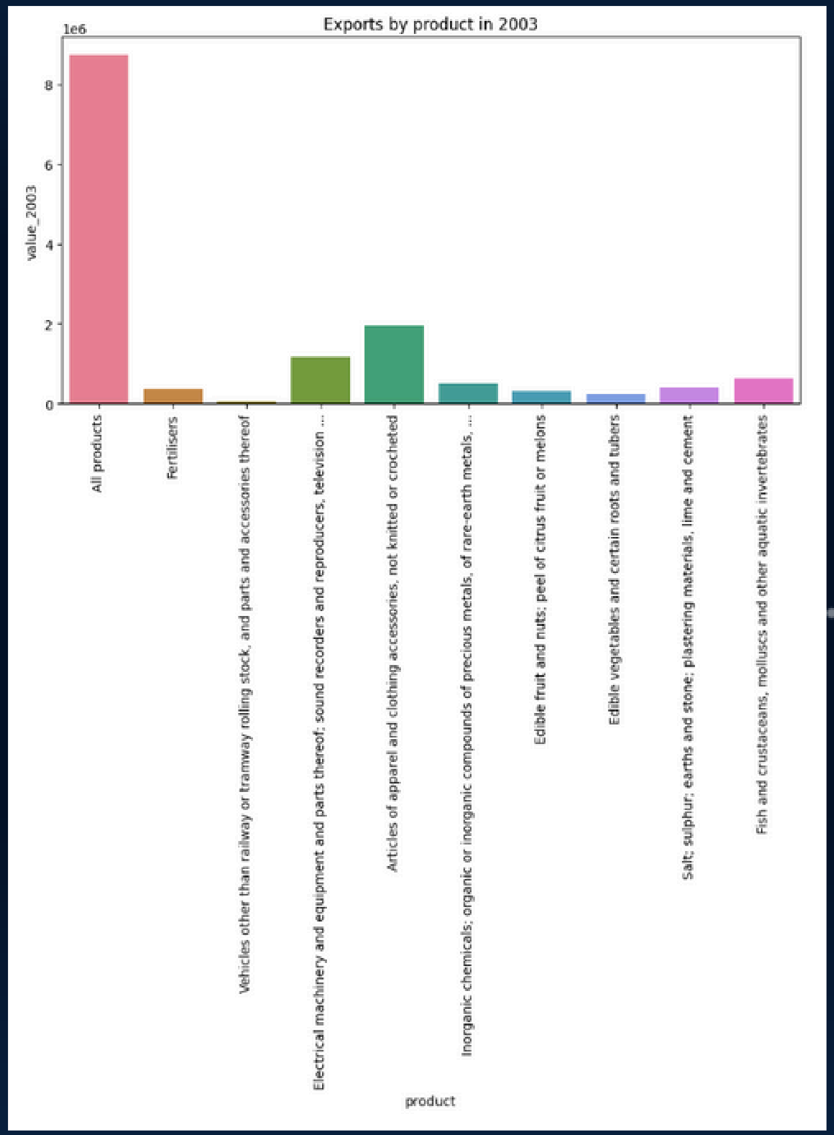


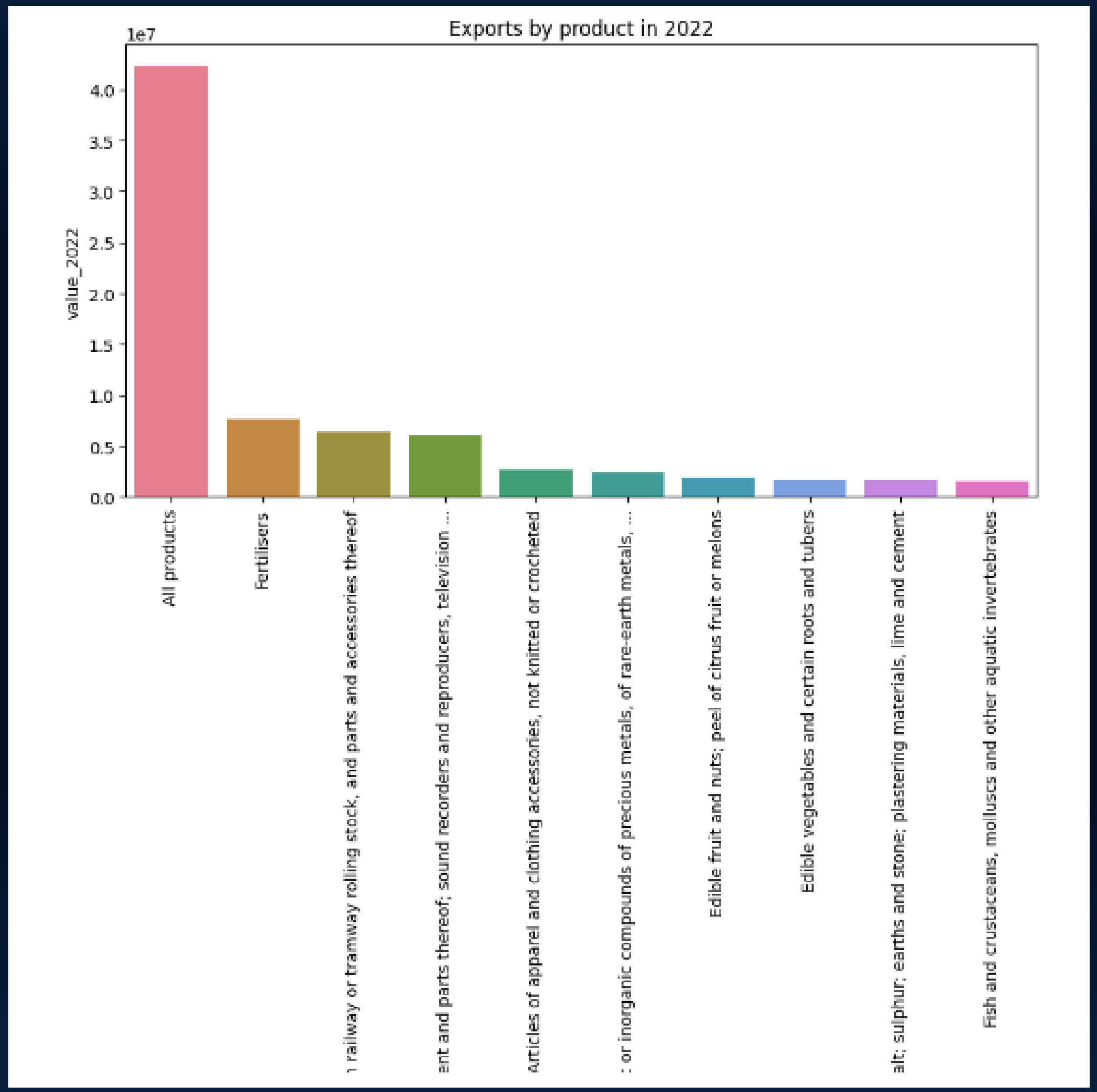
Shows export data for first 20 products, plotting value growth over time.

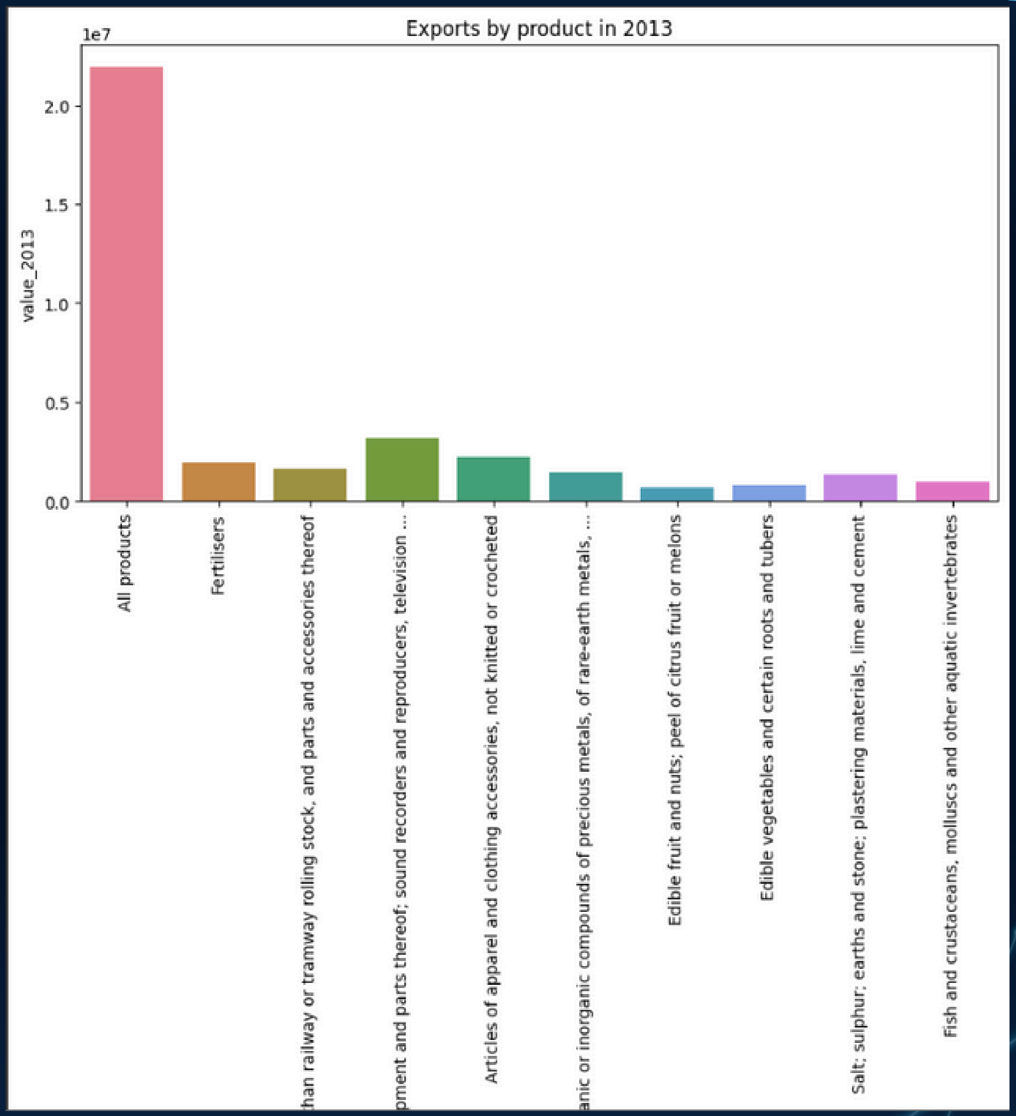


Organizing export data for first 20 products into subplots to illustrate value changes over time.

Data visualisation







Visualize exports by product using a color palette, assigning a unique color to each bar.

Data Cleaning and Preprocessing

```
transitional_data.head()
```

	product	value_2003	value_2004	value_2005	value_2006	value_2007	value_2008	value_2009	value_2010	value_2011	...	growth_2012	growth_2013	growth_2014	growth_2015	growth_2016	growth_2017	growth_2018	growth_2019	growth_2020	growth_2021
0	All products	8738341	9870179	11197413	12731303	15321255	20094617	14027369	17764791	21649934	...	3.0	8.0	-7.0	3.0	12.0	14.0	1.0	-6.0	32.0	16.0
1	Fertilisers	371608	431325	444344	533674	876747	1412452	697642	1561945	2317995	...	-20.0	7.0	-9.0	14.0	21.0	23.0	-8.0	16.0	69.0	35.0
2	Vehicles other than railway or tramway rolling...	46680	55256	76111	117890	161777	201129	223629	245346	426212	...	66.0	50.0	8.0	19.0	8.0	14.0	-1.0	-6.0	39.0	26.0
3	Electrical machinery and equipment and parts t...	1176179	1257912	1599657	1930282	2359746	2504401	1998575	2632491	3172824	...	12.0	19.0	-7.0	7.0	13.0	17.0	8.0	-12.0	13.0	14.0
4	Articles of apparel and clothing accessories, ...	1952757	2116194	2040800	2377490	2532616	2483422	2236326	2142622	2280072	...	0.0	6.0	-14.0	9.0	7.0	5.0	-4.0	-21.0	32.0	8.0

5 rows × 60 columns

```
transitional_df.describe()
```

	value_2003	value_2004	value_2005	value_2006	value_2007	value_2008	value_2009	value_2010	value_2011	value_2012	...	growth_2012	growth_2013	growth_2014	growth_2015	growth_2016	growth_2017	growth_2018	growth_2019	growth_2020	growth_2021
count	9.800000e+01	9.800000e+01	9.800000e+01	9.800000e+01	9.800000e+01	9.800000e+01	9.800000e+01	9.800000e+01	9.800000e+01	9.800000e+01	...	96.000000	96.000000	97.000000	97.000000	97.000000	97.000000	97.000000	97.000000	96.000000	95.000000
mean	1.783335e+05	2.014323e+05	2.285186e+05	2.598225e+05	3.126787e+05	4.100942e+05	2.862728e+05	3.625467e+05	4.418354e+05	4.370854e+05	...	39.197917	28.197917	-8.938144	80.226804	56.958763	180.690722	4.835052	3.402062	39.281250	15.578947
std	9.112747e+05	1.025980e+06	1.159090e+06	1.318700e+06	1.583579e+06	2.081394e+06	1.445491e+06	1.828460e+06	2.231009e+06	2.203461e+06	...	262.101170	76.776726	50.576430	464.549233	370.709958	1131.951278	66.558665	90.900204	77.077364	61.093159
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	...	-90.000000	-89.000000	-100.000000	-98.000000	-94.000000	-87.000000	-92.000000	-100.000000	-100.000000	-77.000000
25%	1.920250e+03	1.464500e+03	3.471000e+03	5.006750e+03	5.985000e+03	6.472500e+03	4.936250e+03	6.190750e+03	6.190250e+03	6.659000e+03	...	-16.250000	-1.250000	-28.000000	-7.000000	-1.000000	0.000000	-11.000000	-21.000000	4.750000	-5.500000
50%	1.313200e+04	1.690100e+04	1.882900e+04	2.399000e+04	2.443850e+04	2.651550e+04	2.330050e+04	3.067950e+04	2.719300e+04	2.725550e+04	...	5.500000	16.000000	-11.000000	6.000000	11.000000	14.000000	-1.000000	-6.000000	25.000000	7.000000
75%	4.119425e+04	4.821850e+04	5.780675e+04	6.796100e+04	8.801100e+04	9.365950e+04	8.859300e+04	1.162568e+05	9.738800e+04	1.196208e+05	...	24.250000	37.250000	3.000000	17.000000	25.000000	37.000000	11.000000	11.000000	47.250000	23.500000
max	8.738341e+06	9.870179e+06	1.119741e+07	1.273130e+07	1.532126e+07	2.009462e+07	1.402737e+07	1.776479e+07	2.164993e+07	2.141718e+07	...	2488.000000	445.000000	344.000000	4000.000000	3563.000000	9233.000000	583.000000	791.000000	521.000000	501.000000

8 rows × 59 columns

Provides a statistical summary for each column, including values from 2003 to 2022 of the DataFrame

Data Cleaning

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 98 entries, 0 to 97
Data columns (total 60 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   product       98 non-null     object
 1   value_2003    98 non-null     int64
 2   value_2004    98 non-null     int64
 3   value_2005    98 non-null     int64
 4   value_2006    98 non-null     int64
 5   value_2007    98 non-null     int64
 6   value_2008    98 non-null     int64
 7   value_2009    98 non-null     int64
 8   value_2010    98 non-null     int64
 9   value_2011    98 non-null     int64
 10  value_2012    98 non-null     int64
 11  value_2013    98 non-null     int64
 12  value_2014    98 non-null     int64
 13  value_2015    98 non-null     int64
 14  value_2016    98 non-null     int64
 15  value_2017    98 non-null     int64
 16  value_2018    98 non-null     int64
 17  value_2019    98 non-null     int64
 18  value_2020    98 non-null     int64
 19  value_2021    98 non-null     int64
 20  value_2022    98 non-null     int64
 21  share_2003    98 non-null     float64
 22  share_2004    98 non-null     float64
 23  share_2005    98 non-null     float64
 24  share_2006    98 non-null     float64
 25  share_2007    98 non-null     float64
 26  share_2008    98 non-null     float64
 27  share_2009    98 non-null     float64
 28  share_2010    98 non-null     float64
 29  share_2011    98 non-null     float64
 30  share_2012    98 non-null     float64
 31  share_2013    98 non-null     float64
 32  share_2014    98 non-null     float64
 33  share_2015    98 non-null     float64
 34  share_2016    98 non-null     float64
 35  share_2017    98 non-null     float64
 36  share_2018    98 non-null     float64
 37  share_2019    98 non-null     float64
 38  share_2020    98 non-null     float64
 39  share_2021    98 non-null     float64
 40  share_2022    98 non-null     float64
 41  growth_2003   96 non-null     float64
 42  growth_2004   97 non-null     float64
 43  growth_2005   96 non-null     float64
 44  growth_2006   97 non-null     float64
 45  growth_2007   97 non-null     float64
 46  growth_2008   97 non-null     float64
 47  growth_2009   97 non-null     float64
 48  growth_2010   97 non-null     float64
 49  growth_2011   97 non-null     float64
 50  growth_2012   96 non-null     float64
 51  growth_2013   96 non-null     float64
 52  growth_2014   97 non-null     float64
 53  growth_2015   97 non-null     float64
 54  growth_2016   97 non-null     float64
 55  growth_2017   97 non-null     float64
 56  growth_2018   97 non-null     float64
 57  growth_2019   97 non-null     float64
 58  growth_2020   96 non-null     float64
 59  growth_2021   95 non-null     float64
dtypes: float64(39), int64(20), object(1)
memory usage: 46.1+ KB
```

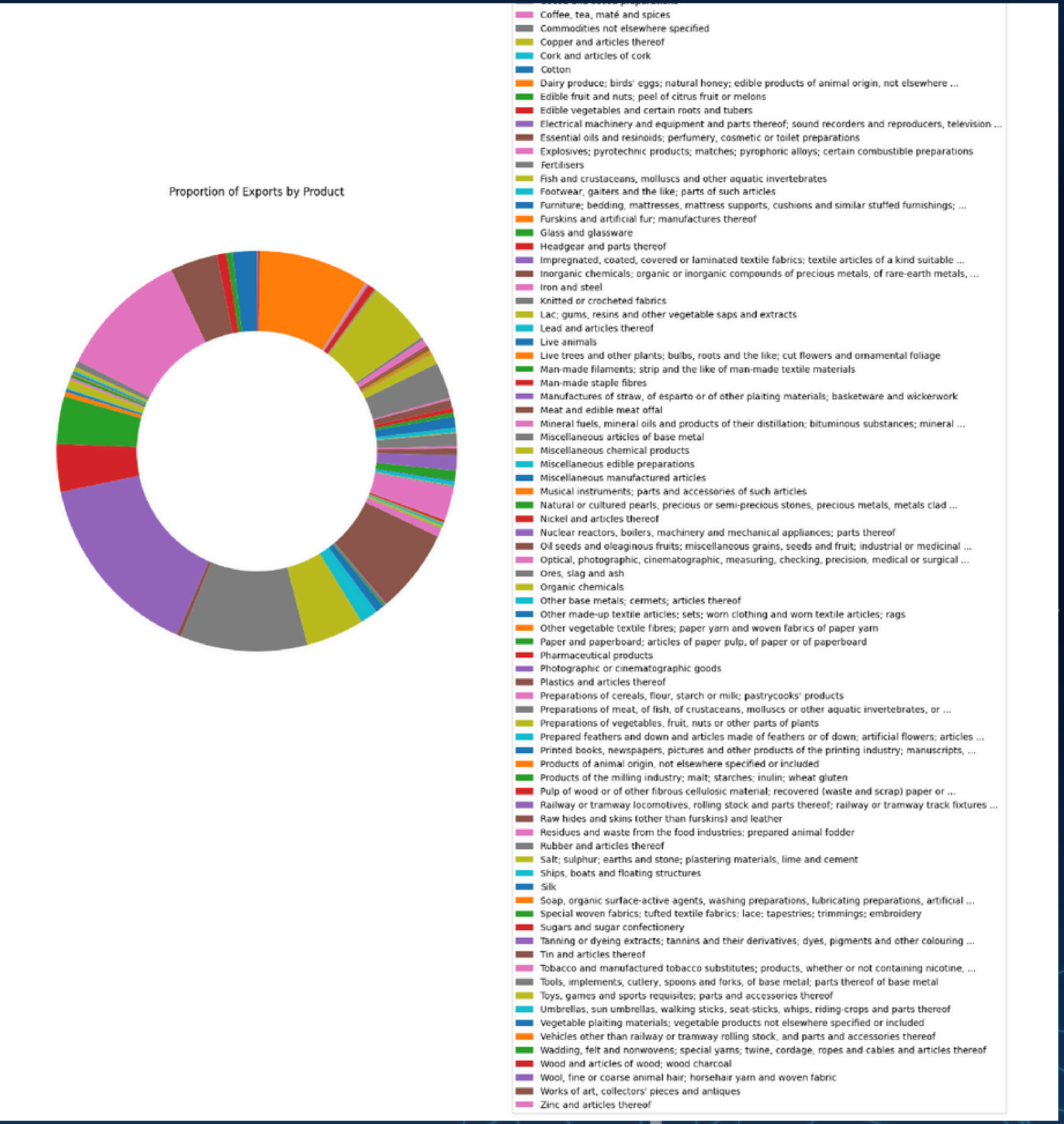
```
#Check the count of missing values in the time series data
time_series.isna().sum()
```

```
product    0
year       0
value      0
share      0
dtype: int64
```

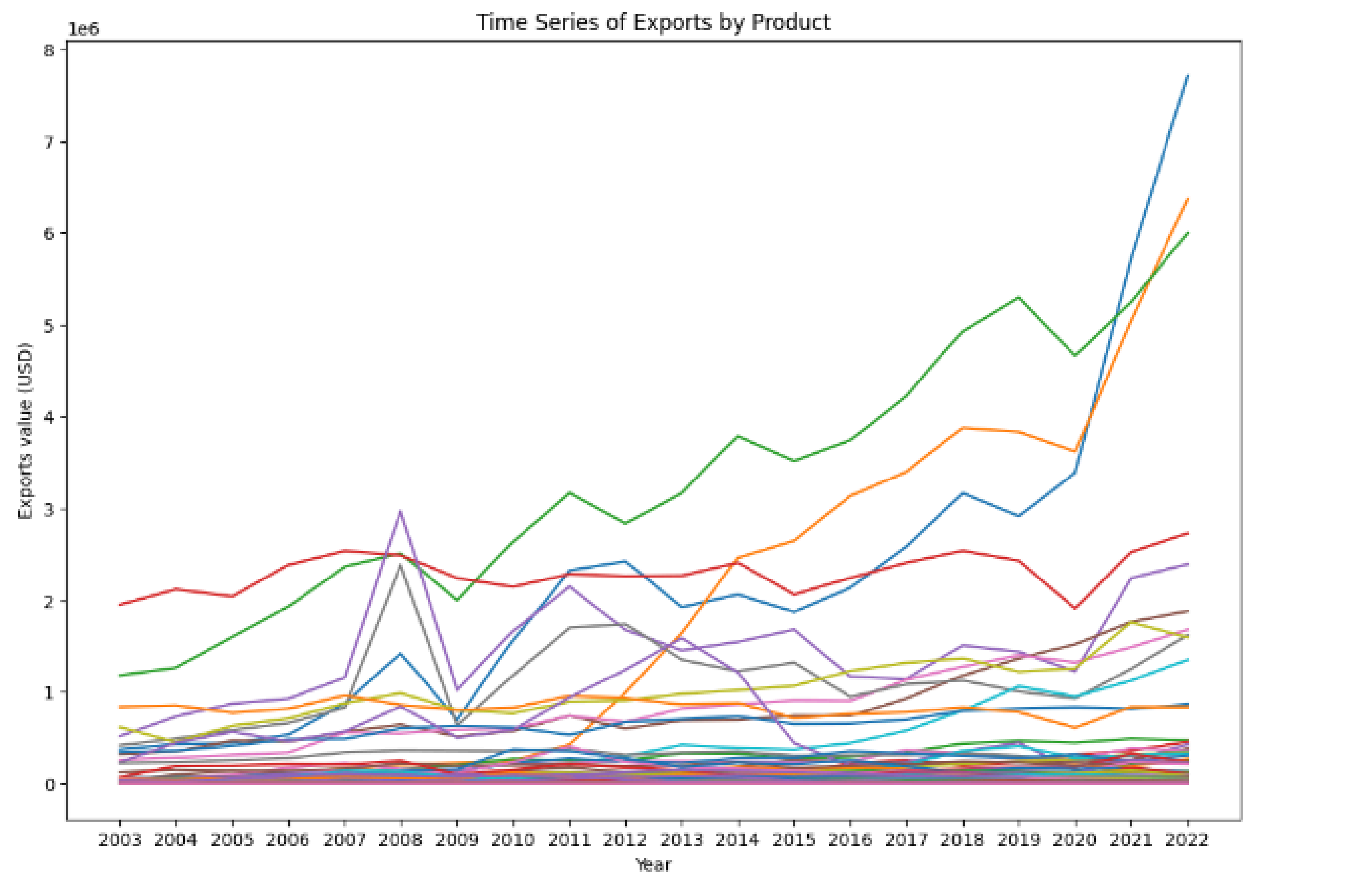
Generates yearly time series data for each product, ensuring accuracy by removing the initial row, then checks for missing values.

Proportion of Exports by Product

generates a donut chart to depict the proportion of exports for each product using Matplotlib.

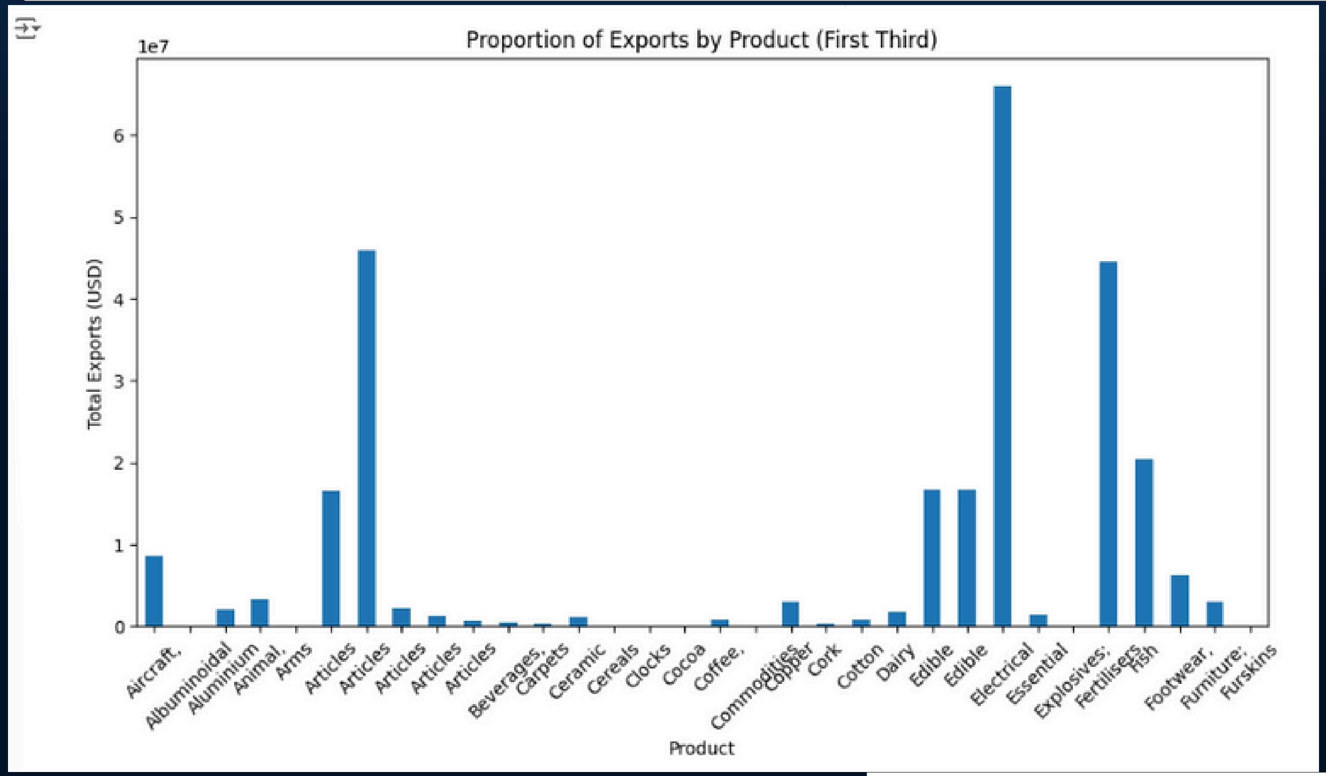


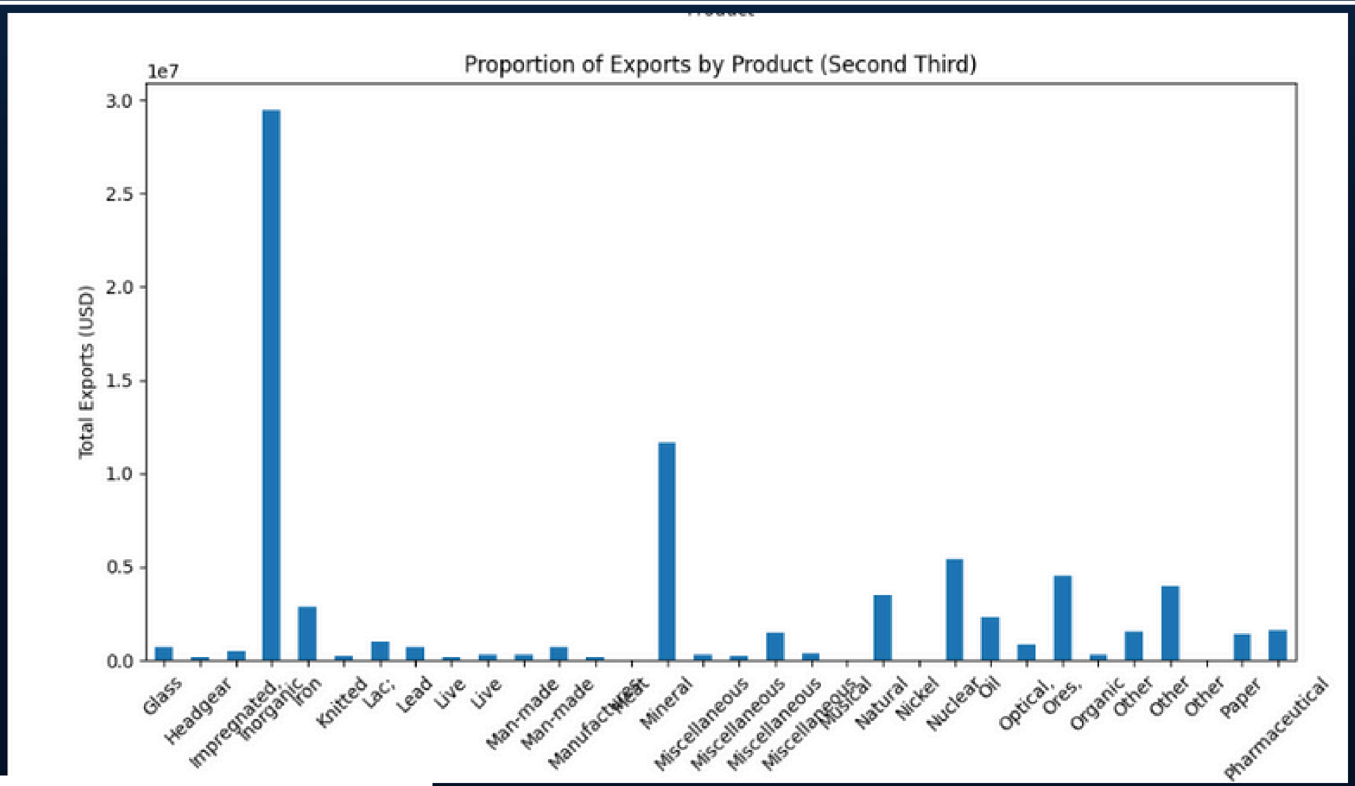
Plot the export time series for each product

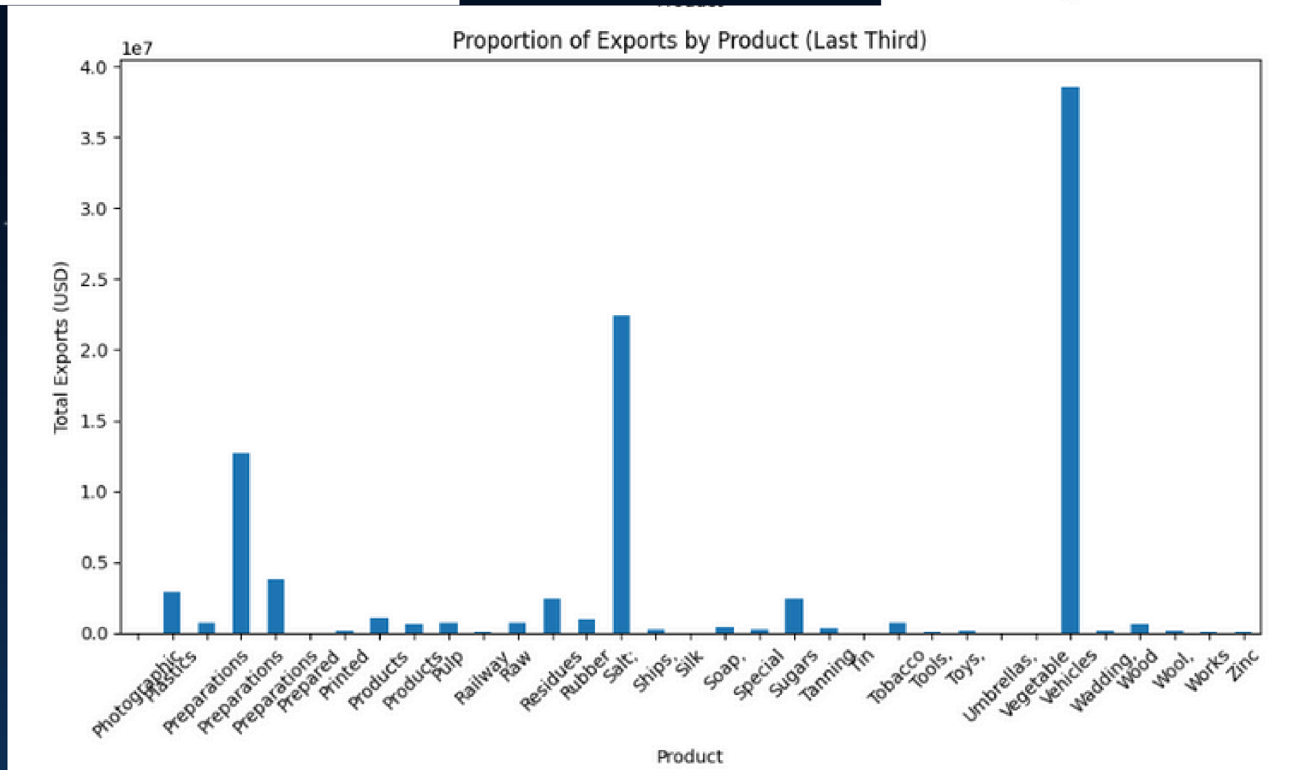


Visualizing the time series of exports for each product over the years.

Processed Data







Divide products into three groups and visualize their export proportions through bar charts

04

Model

The first Model

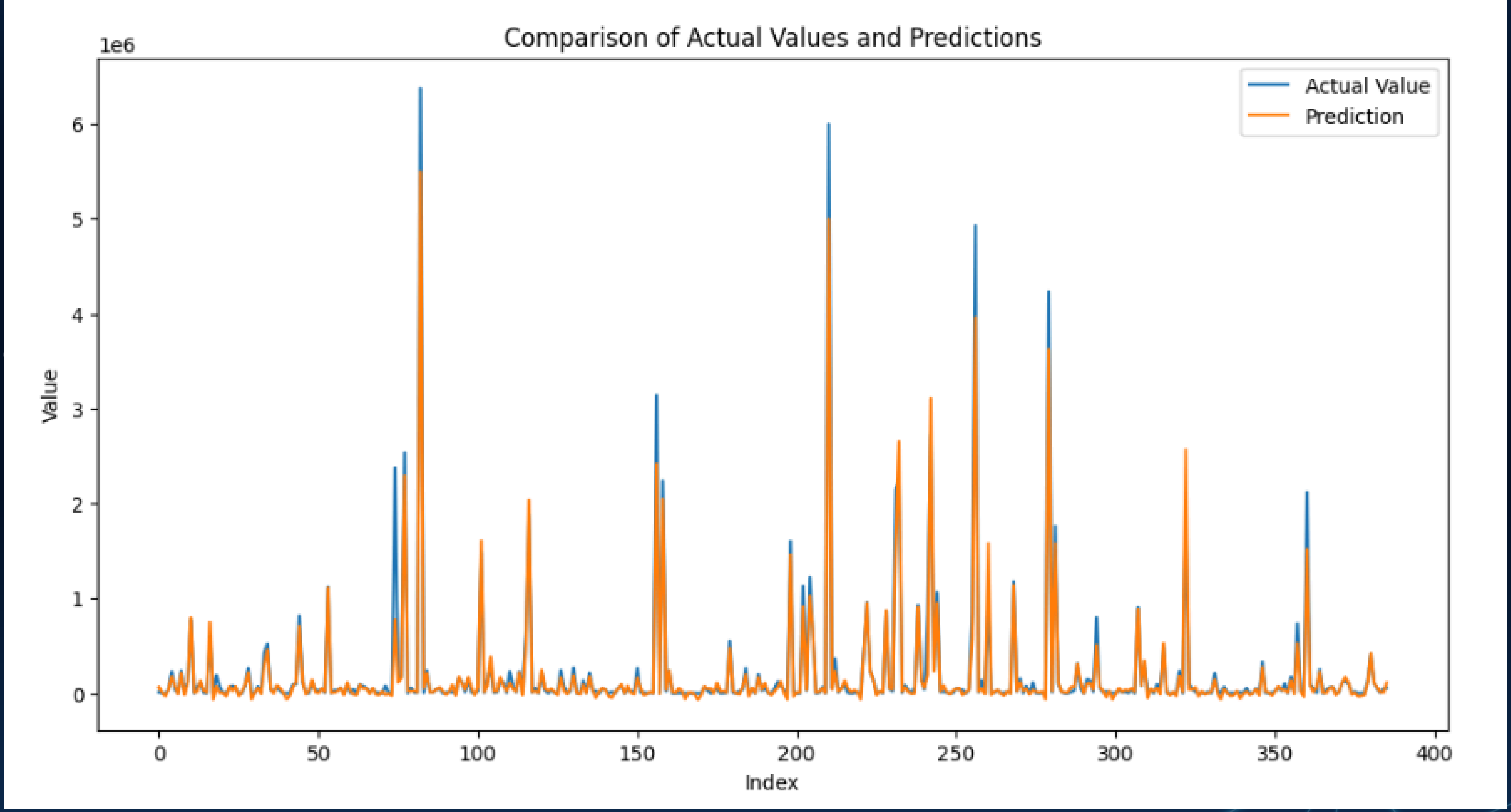
First, we load preprocessed data, normalize it, and generate temporal sequences for model training. Then, an RNN, specifically LSTM, is utilized for its capability in capturing temporal dependencies. The data is divided into training and testing sets, and a simple RNN model with one LSTM layer and a dense output layer is established. Early stopping is employed to prevent overfitting, followed by training and evaluation on the test set.

Train and Test The Model

```
Epoch 1/100
44/44 [==============================] - 3s 18ms/step - loss: 0.0454 - val_loss: 0.0315
Epoch 2/100
44/44 [==============================] - 0s 6ms/step - loss: 0.0284 - val_loss: 0.0256
Epoch 3/100
44/44 [==============================] - 0s 7ms/step - loss: 0.0199 - val_loss: 0.0175
Epoch 4/100
44/44 [==============================] - 0s 7ms/step - loss: 0.0163 - val_loss: 0.0174
Epoch 5/100
44/44 [==============================] - 0s 7ms/step - loss: 0.0158 - val_loss: 0.0156
Epoch 6/100
44/44 [==============================] - 0s 7ms/step - loss: 0.0150 - val_loss: 0.0157
Epoch 7/100
44/44 [==============================] - 0s 7ms/step - loss: 0.0143 - val_loss: 0.0143
Epoch 8/100
44/44 [==============================] - 0s 6ms/step - loss: 0.0140 - val_loss: 0.0136
Epoch 9/100
44/44 [==============================] - 0s 6ms/step - loss: 0.0130 - val_loss: 0.0125
Epoch 10/100
44/44 [==============================] - 0s 7ms/step - loss: 0.0117 - val_loss: 0.0114
Epoch 11/100
44/44 [==============================] - 0s 7ms/step - loss: 0.0106 - val_loss: 0.0123
Epoch 12/100
44/44 [==============================] - 0s 7ms/step - loss: 0.0101 - val_loss: 0.0090
Epoch 13/100
...
Prédiction: [2.0111017e+03 1.1182324e+05 2.5436863e-01]
Valeur réelle: [2.011e+03 5.854e+04 2.700e-01]
----------------------------------------
Mean Squared Error: 7968222570.7518835
```

Load data, normalize it, create temporal sequences for model training, split data into training and testing sets, define and train an RNN model, evaluate performance, and make predictions.

Comparison of real values and predictions.



The second Model

ARIMA (AutoRegressive Integrated Moving Average) a classical time series forecasting model that is well-suited for our case for several reasons. Firstly, it enables capturing trends and seasonal patterns present in the demand data for local products. Additionally, ARIMA is robust to non-stationary data, which is often the case in economic time series such as the demand for agricultural products.

The second Model

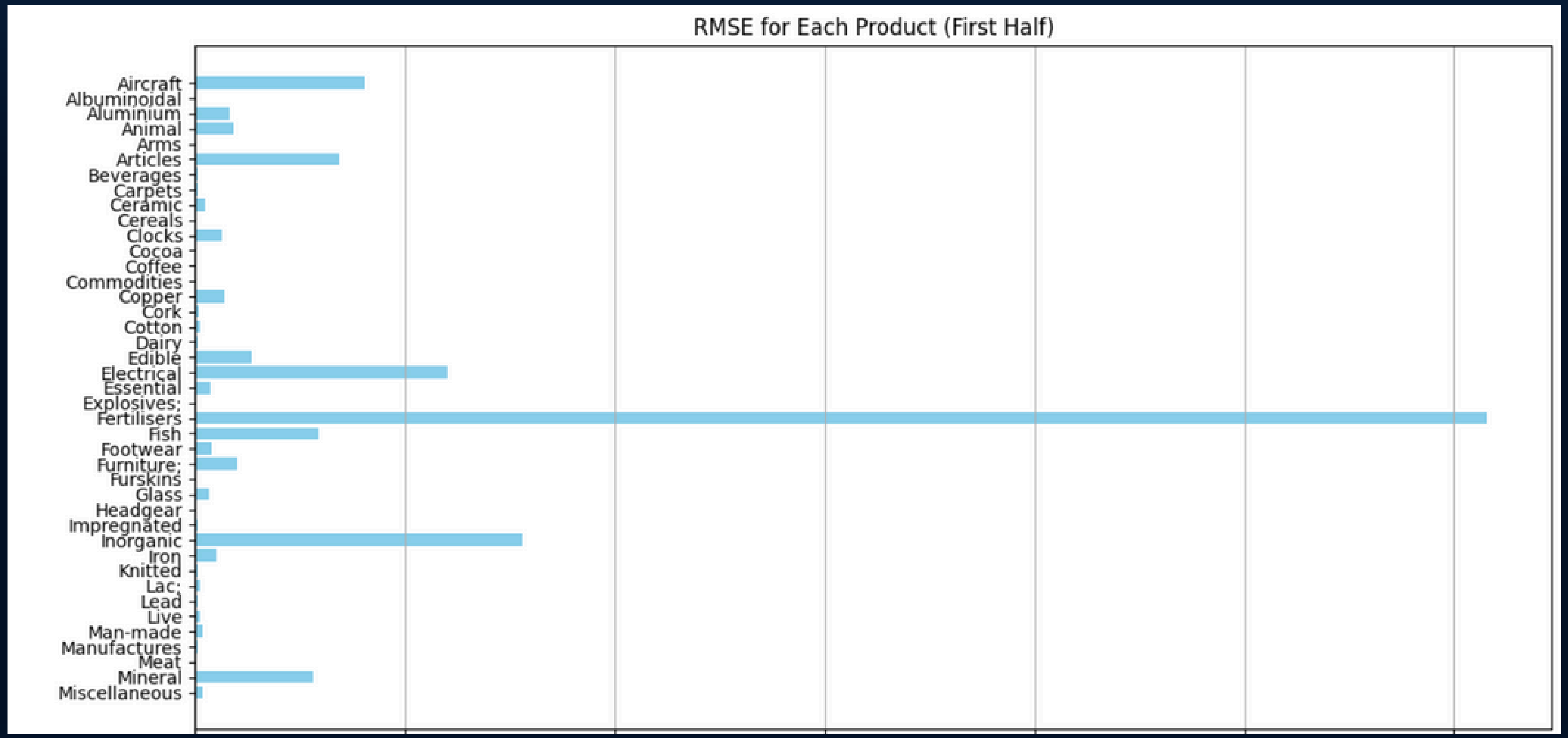
```
Forecasting  Aircraft, spacecraft, and parts thereof
Forecasting  Albuminoidal substances; modified starches; glues; enzymes
Forecasting  Aluminium and articles thereof
Forecasting  Animal, vegetable or microbial fats and oils and their cleavage products; prepared edible fats; ...
Forecasting  Arms and ammunition; parts and accessories thereof
Forecasting  Articles of apparel and clothing accessories, knitted or crocheted
Forecasting  Articles of apparel and clothing accessories, not knitted or crocheted
Forecasting  Articles of iron or steel
Forecasting  Articles of leather; saddlery and harness; travel goods, handbags and similar containers; articles ...
Forecasting  Articles of stone, plaster, cement, asbestos, mica or similar materials
Forecasting  Beverages, spirits and vinegar
Forecasting  Carpets and other textile floor coverings
Forecasting  Ceramic products
Forecasting  Cereals
Forecasting  Clocks and watches and parts thereof
Forecasting  Cocoa and cocoa preparations
Forecasting  Coffee, tea, maté and spices
Forecasting  Commodities not elsewhere specified
Forecasting  Copper and articles thereof
Forecasting  Cork and articles of cork
Forecasting  Cotton
Forecasting  Dairy produce; birds' eggs; natural honey; edible products of animal origin, not elsewhere ...
Forecasting  Edible fruit and nuts; peel of citrus fruit or melons
Forecasting  Edible vegetables and certain roots and tubers
Forecasting  Electrical machinery and equipment and parts thereof; sound recorders and reproducers, television ...
...
Forecasting  Wood and articles of wood; wood charcoal
Forecasting  Wool, fine or coarse animal hair; horsehair yarn and woven fabric
Forecasting  Works of art, collectors' pieces and antiques
Forecasting  Zinc and articles thereof
```

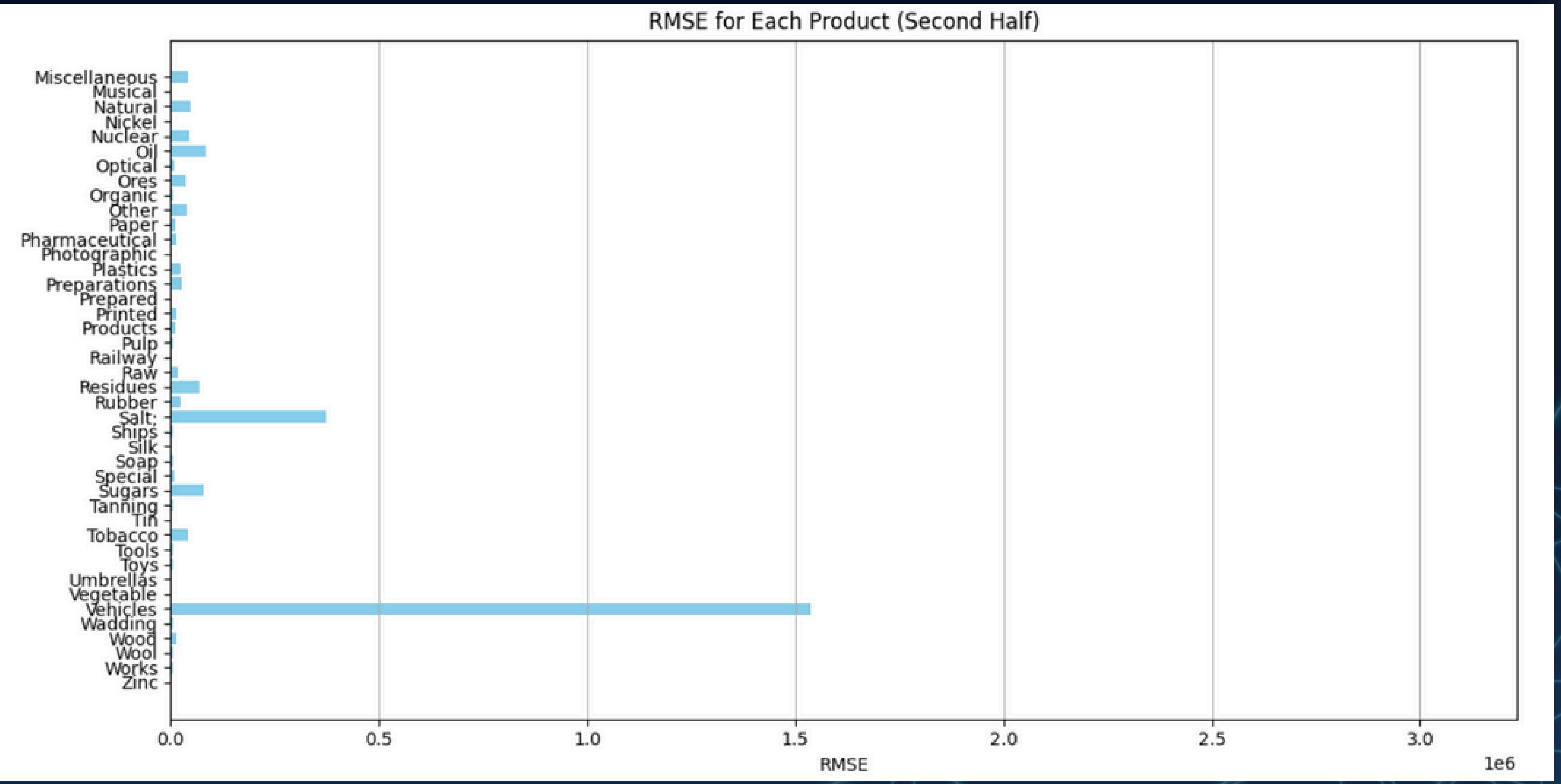
List of products to forecast demand, storing the forecast, actual values, and error for each product.

Model Prediction

```
Product:  Aircraft, spacecraft, and parts thereof
RMSE:  403424.0398328307
---------------------------------------
Product:  Albuminoidal substances; modified starches; glues; enzymes
RMSE:  732.3753893244749
---------------------------------------
Product:  Aluminium and articles thereof
RMSE:  82937.18182234194
---------------------------------------
Product:  Animal, vegetable or microbial fats and oils and their cleavage products; prepared edible fats; ...
RMSE:  90344.75632482184
---------------------------------------
Product:  Arms and ammunition; parts and accessories thereof
RMSE:  295.55934772062557
---------------------------------------
Product:  Articles of apparel and clothing accessories, knitted or crocheted
RMSE:  110960.1803074277
---------------------------------------
Product:  Articles of apparel and clothing accessories, not knitted or crocheted
RMSE:  342616.39125152037
---------------------------------------
Product:  Articles of iron or steel
RMSE:  59715.20676845658
---------------------------------------
Product:  Articles of leather; saddlery and harness; travel goods, handbags and similar containers; articles ...
...
Product:  Zinc and articles thereof
RMSE:  2123.197528564087
---------------------------------------
Overall RMSE:  99609.54688945597
```

Comparison of RMSE





Divides products into two groups and creates horizontal bar charts to visualize the RMSE (Root Mean Squared Error) for each product in each group, facilitating comparison of forecasting accuracy.

Conclusion

Our data-driven approach, utilizing techniques like ARIMA and LSTM-based RNNs, forecasted demand for Moroccan local products. Through thorough analysis, we provided valuable insights into demand trends, empowering industry stakeholders with actionable information. By identifying market dynamics and influential factors, our findings enable informed decision-making in production, distribution, and market positioning, enhancing competitiveness and sustainability in the Moroccan local products industry.

Thanks!