231501506

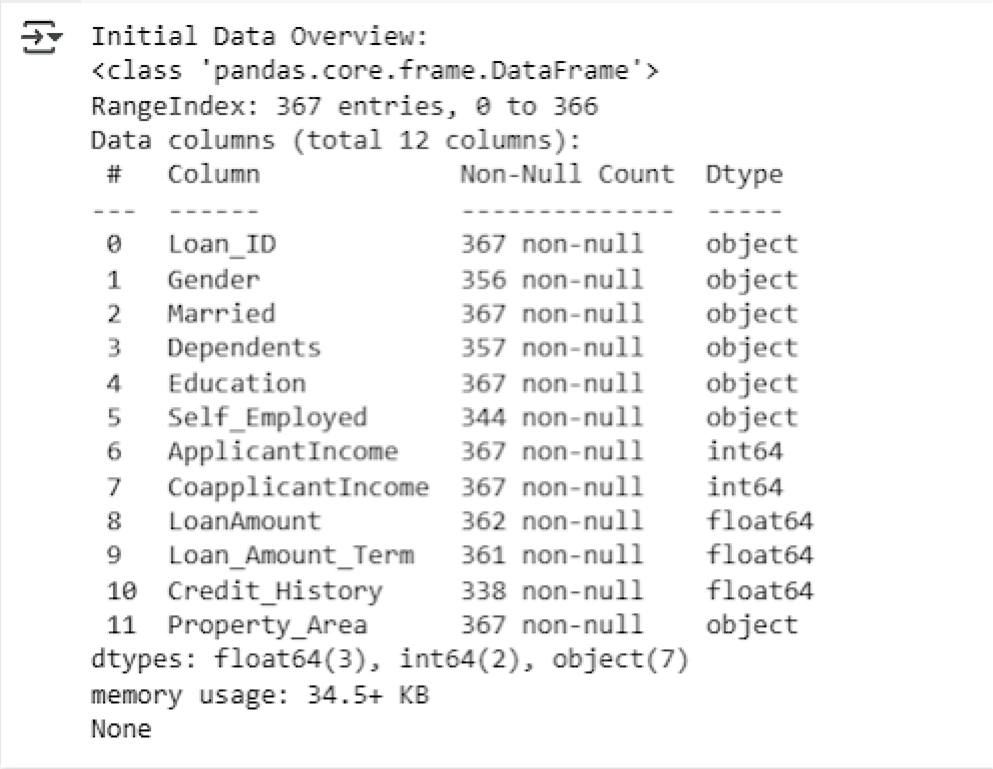
EX:3	EDA-Data Cleaning	AD23632

Aim:

- Handling missing values: detection, filling, and dropping
- Removing duplicates and unnecessary data
- Data type conversion and ensuring consistency
- Normalize data (e.g., standardization, min-max scaling).

CODE:

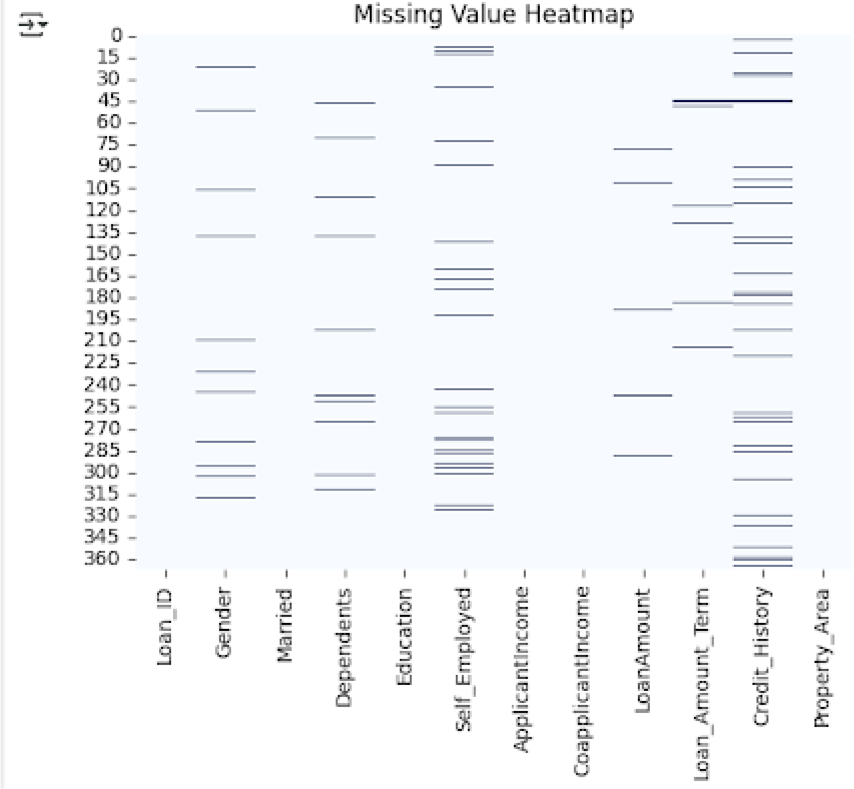
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler, StandardScaler
df = pd.read_csv('/content/test_Y3wMUE5_7gLdaTN.csv')
print("Initial Data Overview:")
print(df.info())
```

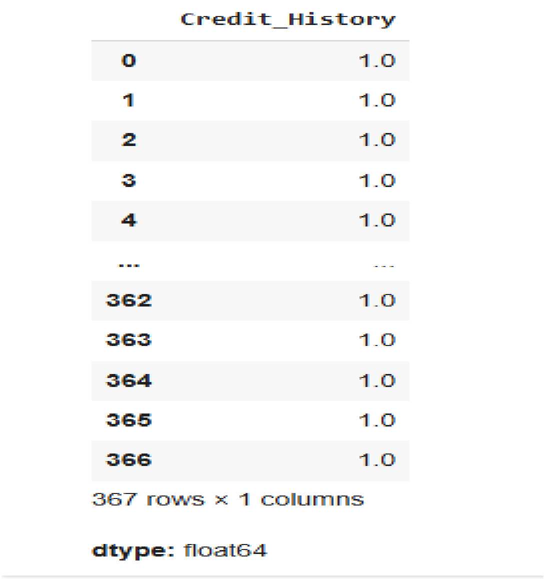


```
Initial Data Overview:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 367 entries, 0 to 366
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            367 non-null    object
 1   Gender             356 non-null    object
 2   Married            367 non-null    object
 3   Dependents         357 non-null    object
 4   Education          367 non-null    object
 5   Self_Employed      344 non-null    object
 6   ApplicantIncome    367 non-null    int64
 7   CoapplicantIncome  367 non-null    int64
 8   LoanAmount         362 non-null    float64
 9   Loan_Amount_Term   361 non-null    float64
 10  Credit_History     338 non-null    float64
 11  Property_Area      367 non-null    object
dtypes: float64(3), int64(2), object(7)
memory usage: 34.5+ KB
None
```

```
print("\nMissing Values in Each Column:\n", df.isnull().sum())
sns.heatmap(df.isnull(), cbar=False, cmap="Blues")
```

```
plt.title("Missing Value Heatmap")
plt.show()
for col in ['Gender', 'Married', 'Dependents', 'Self_Employed']:
    df[col].fillna(df[col].mode()[0])
df['LoanAmount'].fillna(df['LoanAmount'].median())
df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0])
df['Credit_History'].fillna(df['Credit_History'].mode()[0])
```





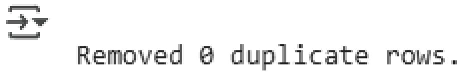
	Credit_History
0	1.0
1	1.0
2	1.0
3	1.0
4	1.0
...	...
362	1.0
363	1.0
364	1.0
365	1.0
366	1.0

367 rows × 1 columns

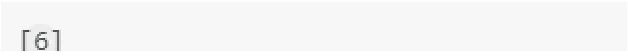
dtype: float64

```
initial_rows = df.shape[0]
```

```
df.drop_duplicates(inplace=True)
print(f"\nRemoved {initial_rows - df.shape[0]} duplicate rows.")
```

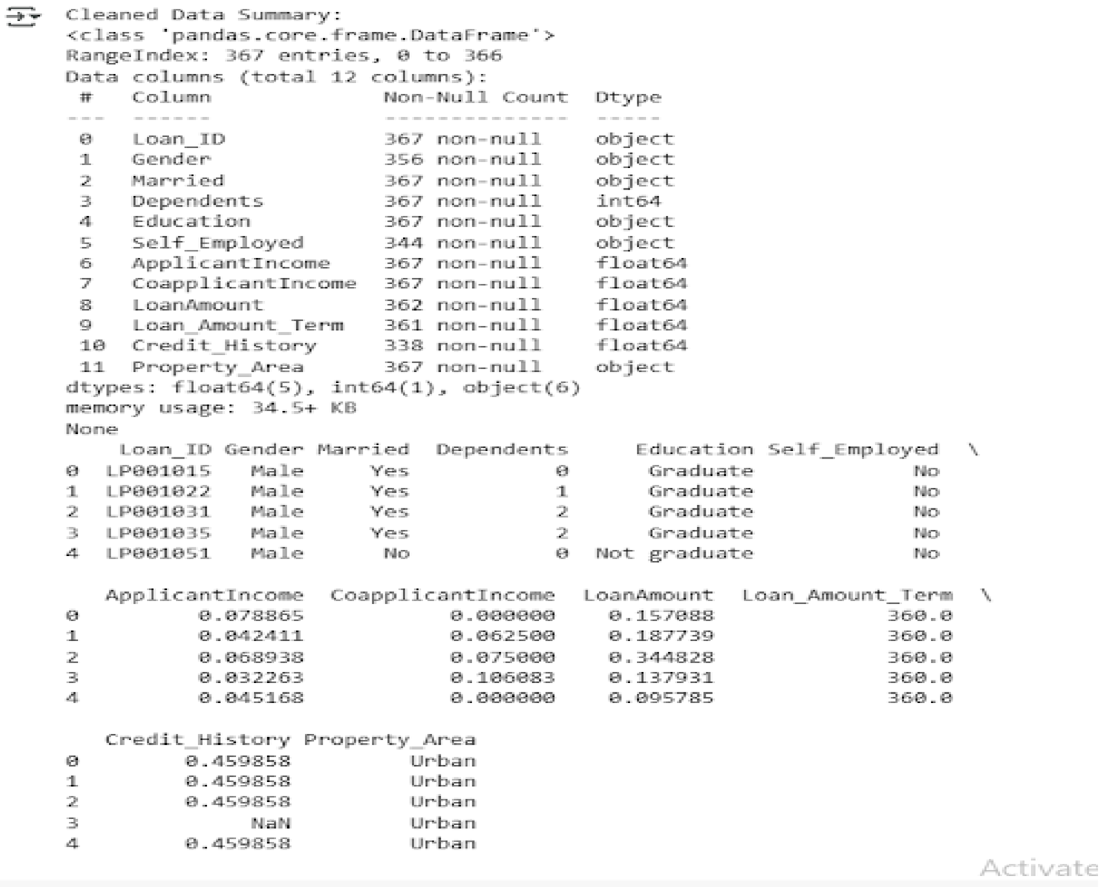


```
Removed 0 duplicate rows.
```



```
[6]
```

```
df['Dependents'] = df['Dependents'].replace('3+', 3).fillna(0).astype(int)
for col in ['Gender', 'Married', 'Education', 'Self_Employed', 'Property_Area']:
    df[col] = df[col].str.strip().str.capitalize()
min_max_scaler = MinMaxScaler()
scale_cols = ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount']
df[scale_cols] = min_max_scaler.fit_transform(df[scale_cols])
scaler = StandardScaler()
df[['Credit_History']] = scaler.fit_transform(df[['Credit_History']])
print("\nCleaned Data Summary:")
print(df.info())
print(df.head())
```



```
Cleaned Data Summary:
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 7   CoapplicantIncome  367 non-null    float64
 8   LoanAmount         362 non-null    float64
 9   Loan_Amount_Term   361 non-null    float64
 10  Credit_History     338 non-null    float64
 11  Property_Area      367 non-null    object
dtypes: float64(5), int64(1), object(6)
memory usage: 34.5+ KB
None
    Loan_ID Gender Married  Dependents     Education Self_Employed  \
0  LP001015   Male     Yes           0      Graduate            No
1  LP001022   Male     Yes           1      Graduate            No
2  LP001031   Male     Yes           2      Graduate            No
3  LP001035   Male     Yes           2      Graduate            No
4  LP001051   Male      No           0  Not graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0         0.078865           0.000000    0.157088             360.0
1         0.042411           0.062500    0.187739             360.0
2         0.068938           0.075000    0.344828             360.0
3         0.032263           0.106083    0.137931             360.0
4         0.045168           0.000000    0.095785             360.0

   Credit_History Property_Area
0        0.459858         Urban
1        0.459858         Urban
2        0.459858         Urban
3             NaN         Urban
4        0.459858         Urban
```

Result:

Thus the EDA-Data Cleaning is done successfully.