

**Sri Sivasubramaniya Nadar College of Engineering, Chennai**  
(An Autonomous Institution affiliated to Anna University)

<b>Degree &amp; Branch</b>	B.E. Computer Science & Engineering
<b>Semester</b>	VI
<b>Subject Code &amp; Name</b>	UCS2612 – Machine Learning Laboratory
<b>Academic Year</b>	2025–2026 (Even)
<b>Batch</b>	2023–2027
<b>Name</b>	Piranow C

**Experiment 1:** Working with Python packages – NumPy, SciPy, Scikit-learn, Matplotlib

**Aim:**

To study and explore Python library packages such as Pandas, NumPy, Matplotlib, Scikit-learn, and SciPy to understand data science and machine learning concepts, and to analyze how datasets are explored and mapped to machine learning models using exploratory data analysis techniques.

**Libraries Used:**

- **NumPy:** Numerical computations and multi-dimensional array handling.
- **Pandas:** Data manipulation, cleaning, and analysis using DataFrames.
- **Matplotlib:** Visualization using line plots, bar charts, and histograms.
- **Seaborn:** Advanced statistical data visualization.
- **Scikit-learn:** Machine learning algorithms, preprocessing, training, and evaluation.
- **SciPy:** Scientific computing, optimization, and statistical analysis.

verbose, tmargin=1in, bmargin=1in, lmargin=1in, rmargin=1in

January 26, 2026

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

from sklearn.model_selection import train_test_split, StratifiedKFold, cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
    confusion_matrix, ConfusionMatrixDisplay,
    silhouette_score, davies_bouldin_score, adjusted_rand_score,
    classification_report
)
from sklearn.decomposition import PCA
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.cluster import KMeans

RANDOM_STATE = 42
```

#IRIS DATASET

```
[2]: df = pd.read_csv("Iris.csv")
df.head()
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

```
[3]: print("Shape:", df.shape)

print("\nInfo:")
df.info()

print("\nSpecies counts:")
print(df["Species"].value_counts())
```

Shape: (150, 6)

Info:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype  
---  --  
 0   Id               150 non-null    int64  
 1   SepalLengthCm    150 non-null    float64 
 2   SepalWidthCm     150 non-null    float64 
 3   PetalLengthCm    150 non-null    float64 
 4   PetalWidthCm     150 non-null    float64 
 5   Species          150 non-null    object  
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

Species counts:

```
Species
Iris-setosa      50
Iris-versicolor  50
Iris-virginica   50
Name: count, dtype: int64
```

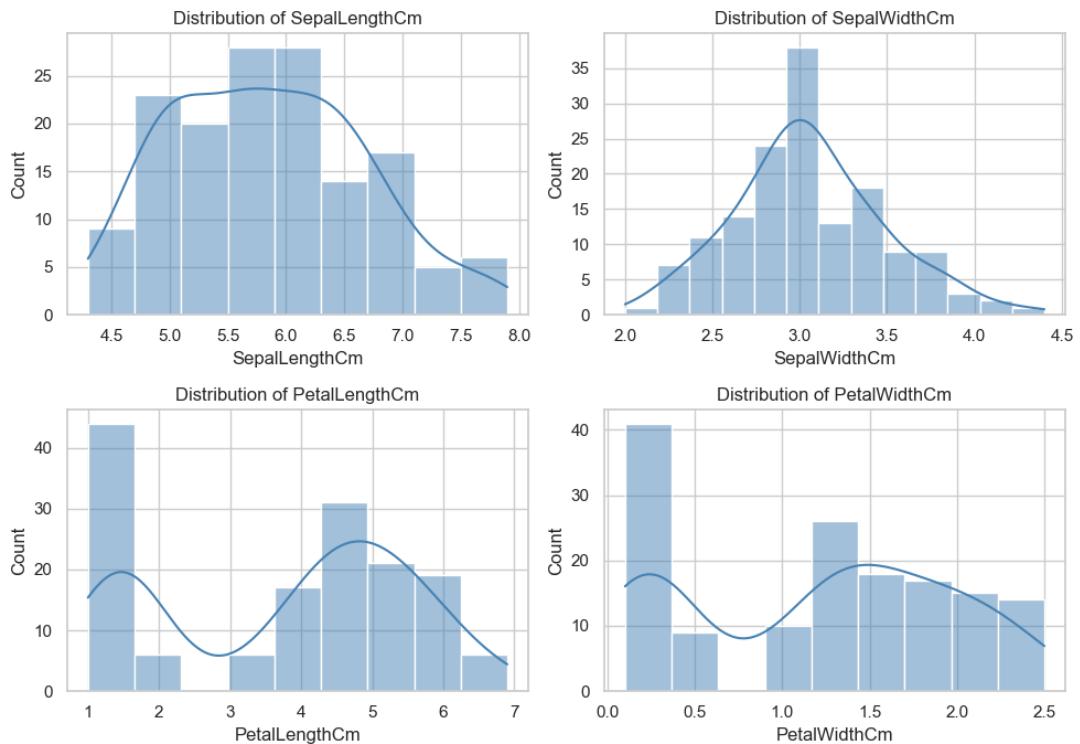
```
[4]: features = ["SepalLengthCm", "SepalWidthCm", "PetalLengthCm", "PetalWidthCm"]
df[features].describe()
```

```
[4]:      SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm
count    150.000000    150.000000    150.000000    150.000000
mean     5.843333     3.054000     3.758667     1.198667
std      0.828066     0.433594     1.764420     0.763161
min      4.300000     2.000000     1.000000     0.100000
25%     5.100000     2.800000     1.600000     0.300000
50%     5.800000     3.000000     4.350000     1.300000
75%     6.400000     3.300000     5.100000     1.800000
max     7.900000     4.400000     6.900000     2.500000
```

```
[5]: sns.set(style="whitegrid")
```

```
fig, axes = plt.subplots(2, 2, figsize=(10, 7))
for ax, col in zip(axes.ravel(), features):
    sns.histplot(df[col], kde=True, ax=ax, color="steelblue")
    ax.set_title(f"Distribution of {col}")

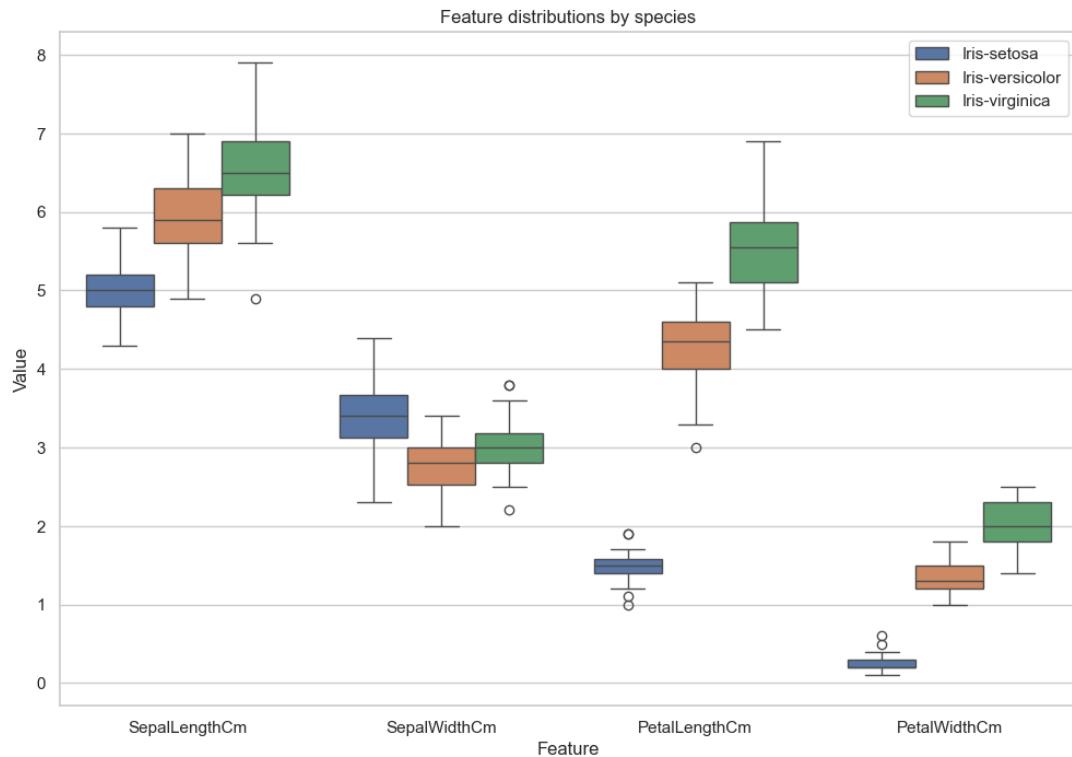
plt.tight_layout()
plt.show()
```



```
[6]: plt.figure(figsize=(12, 8))
```

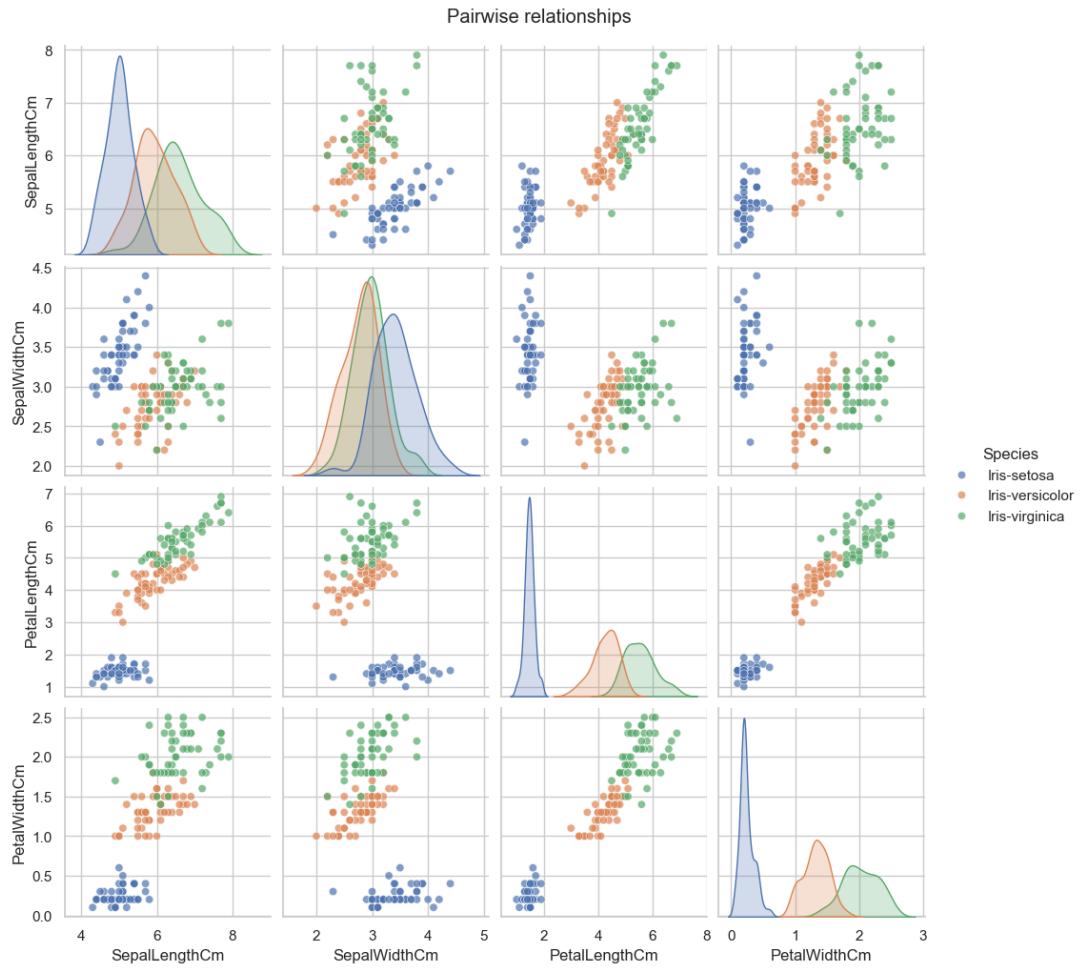
```
melted = df.melt(
    id_vars="Species",
    value_vars=features,
    var_name="Feature",
    value_name="Value"
)

sns.boxplot(data=melted, x="Feature", y="Value", hue="Species")
plt.title("Feature distributions by species")
plt.legend(loc="best")
plt.show()
```



```
[7]: sns.pairplot(
    df,
    hue="Species",
    vars=features,
    diag_kind="kde",
    plot_kws={"alpha": 0.7}
)

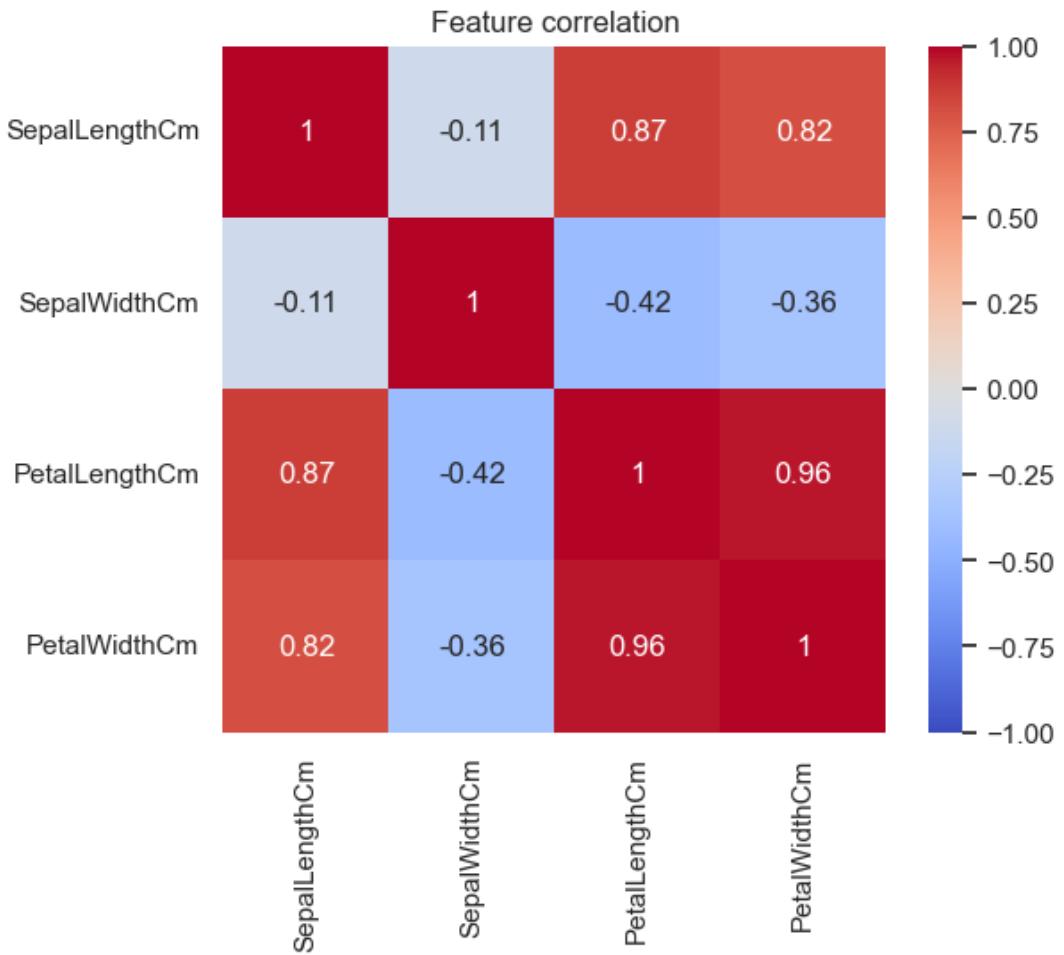
plt.suptitle("Pairwise relationships", y=1.02)
plt.show()
```



```
[8]: plt.figure(figsize=(6, 5))

corr = df[features].corr()
sns.heatmap(corr, annot=True, cmap="coolwarm", vmin=-1, vmax=1)

plt.title("Feature correlation")
plt.show()
```



## #LOAN APPROVAL DATASET

```
[2]: df = pd.read_csv("loan_train.csv")
df.head()
```

```
[2]: Customer ID          Name Gender  Age Income (USD) Income Stability \
0    C-36995  Frederica Shealy      F   56     1933.05        NaN      Low
1    C-33999    America Calderone    M   32     4952.91        NaN      Low
2    C-3770      Rosetta Verne      F   65     988.19        NaN     High
3    C-26480       Zoe Chitty      F   65        NaN        NaN     High
4    C-23459      Afton Venema      F   31     2614.77        NaN      Low

Profession      Type of Employment      Location  Loan Amount Request (USD) \
0    Working           Sales staff  Semi-Urban            72809.58
1    Working             NaN        Semi-Urban            46837.47
2  Pensioner             NaN        Semi-Urban            45593.04
3  Pensioner             NaN         Rural            80057.92
4    Working  High skill tech staff  Semi-Urban            113858.89
```

```

... Credit Score No. of Defaults Has Active Credit Card Property ID \
0 ... 809.44 0 NaN 746
1 ... 780.40 0 Unpossessed 608
2 ... 833.15 0 Unpossessed 546
3 ... 832.70 1 Unpossessed 890
4 ... 745.55 1 Active 715

Property Age Property Type Property Location Co-Applicant \
0 1933.05 4 Rural 1
1 4952.91 2 Rural 1
2 988.19 2 Urban 0
3 NaN 2 Semi-Urban 1
4 2614.77 4 Semi-Urban 1

Property Price Loan Sanction Amount (USD)
0 119933.46 54607.18
1 54791.00 37469.98
2 72440.58 36474.43
3 121441.51 56040.54
4 208567.91 74008.28

```

[5 rows x 24 columns]

```
[3]: print("Shape:", df.shape)

print("\nInfo:")
df.info()

print("\nMissing values per column:")
print(df.isnull().sum())
```

Shape: (30000, 24)

Info:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 24 columns):
 #   Column           Non-Null Count Dtype
 ---  -- 
 0   Customer ID    30000 non-null  object
 1   Name            30000 non-null  object
 2   Gender          29947 non-null  object
 3   Age             30000 non-null  int64
 4   Income (USD)   25424 non-null  float64
```

```

5   Income Stability           28317 non-null  object
6   Profession                 30000 non-null  object
7   Type of Employment         22730 non-null  object
8   Location                   30000 non-null  object
9   Loan Amount Request (USD) 30000 non-null  float64
10  Current Loan Expenses (USD) 29828 non-null  float64
11  Expense Type 1            30000 non-null  object
12  Expense Type 2            30000 non-null  object
13  Dependents                27507 non-null  float64
14  Credit Score               28297 non-null  float64
15  No. of Defaults           30000 non-null  int64
16  Has Active Credit Card    28434 non-null  object
17  Property ID                30000 non-null  int64
18  Property Age               25150 non-null  float64
19  Property Type              30000 non-null  int64
20  Property Location          29644 non-null  object
21  Co-Applicant               30000 non-null  int64
22  Property Price             30000 non-null  float64
23  Loan Sanction Amount (USD) 29660 non-null  float64
dtypes: float64(8), int64(5), object(11)
memory usage: 5.5+ MB

```

Missing values per column:

Customer ID	0
Name	0
Gender	53
Age	0
Income (USD)	4576
Income Stability	1683
Profession	0
Type of Employment	7270
Location	0
Loan Amount Request (USD)	0
Current Loan Expenses (USD)	172
Expense Type 1	0
Expense Type 2	0
Dependents	2493
Credit Score	1703
No. of Defaults	0
Has Active Credit Card	1566
Property ID	0
Property Age	4850
Property Type	0
Property Location	356
Co-Applicant	0

```
Property Price          0
Loan Sanction Amount (USD)    340
dtype: int64
```

```
[4]: df.describe(include="all")
```

	Customer ID	Name	Gender	Age	Income (USD)	\
count	30000	30000	29947	30000.000000	2.542400e+04	
unique	30000	30000	2	NaN	NaN	
top	C-36995	Frederica Shealy	M	NaN	NaN	
freq	1	1	15053	NaN	NaN	
mean	NaN	NaN	NaN	40.092300	2.630574e+03	
std	NaN	NaN	NaN	16.045129	1.126272e+04	
min	NaN	NaN	NaN	18.000000	3.777000e+02	
25%	NaN	NaN	NaN	25.000000	1.650457e+03	
50%	NaN	NaN	NaN	40.000000	2.222435e+03	
75%	NaN	NaN	NaN	55.000000	3.090593e+03	
max	NaN	NaN	NaN	65.000000	1.777460e+06	

	Income	Stability	Profession	Type of Employment	Location	\
count	28317	30000		22730	30000	
unique	2	8		18	3	
top	Low	Working		Laborers	Semi-Urban	
freq	25751	16926		5578	21563	
mean	NaN	NaN		NaN	NaN	
std	NaN	NaN		NaN	NaN	
min	NaN	NaN		NaN	NaN	
25%	NaN	NaN		NaN	NaN	
50%	NaN	NaN		NaN	NaN	
75%	NaN	NaN		NaN	NaN	
max	NaN	NaN		NaN	NaN	

	Loan Amount	Request (USD)	...	Credit Score	No. of Defaults	\
count		30000.000000	...	28297.000000	30000.000000	
unique		NaN	...	NaN	NaN	
top		NaN	...	NaN	NaN	
freq		NaN	...	NaN	NaN	
mean		88826.333855	...	739.885381	0.193933	
std		59536.949605	...	72.163846	0.395384	
min		6048.240000	...	580.000000	0.000000	
25%		41177.755000	...	681.880000	0.000000	
50%		75128.075000	...	739.820000	0.000000	
75%		119964.605000	...	799.120000	0.000000	
max		621497.820000	...	896.260000	1.000000	

	Has Active Credit Card	Property ID	Property Age	Property Type	\
count	28434	30000.000000	2.515000e+04	30000.000000	
unique	3	NaN	NaN	NaN	
top	Active	NaN	NaN	NaN	
freq	9771	NaN	NaN	NaN	
mean	NaN	501.934700	2.631119e+03	2.460067	
std	NaN	288.158086	1.132268e+04	1.118562	
min	NaN	1.000000	3.777000e+02	1.000000	
25%	NaN	251.000000	1.650450e+03	1.000000	
50%	NaN	504.000000	2.223250e+03	2.000000	
75%	NaN	751.000000	3.091408e+03	3.000000	
max	NaN	999.000000	1.777460e+06	4.000000	
	Property Location	Co-Applicant	Property Price	\	
count	29644	30000.000000	3.000000e+04		
unique	3	NaN	NaN		
top	Semi-Urban	NaN	NaN		
freq	10387	NaN	NaN		
mean	NaN	-4.743867	1.317597e+05		
std	NaN	74.614593	9.354955e+04		
min	NaN	-999.000000	-9.990000e+02		
25%	NaN	1.000000	6.057216e+04		
50%	NaN	1.000000	1.099936e+05		
75%	NaN	1.000000	1.788807e+05		
max	NaN	1.000000	1.077967e+06		
	Loan Sanction Amount (USD)				
count	29660.000000				
unique		NaN			
top		NaN			
freq		NaN			
mean	47649.342208				
std	48221.146686				
min	-999.000000				
25%	0.000000				
50%	35209.395000				
75%	74261.250000				
max	481907.320000				

[11 rows x 24 columns]

```
[5]: numeric_cols = df.select_dtypes(include=["int64", "float64"]).columns
n_cols = 2
```

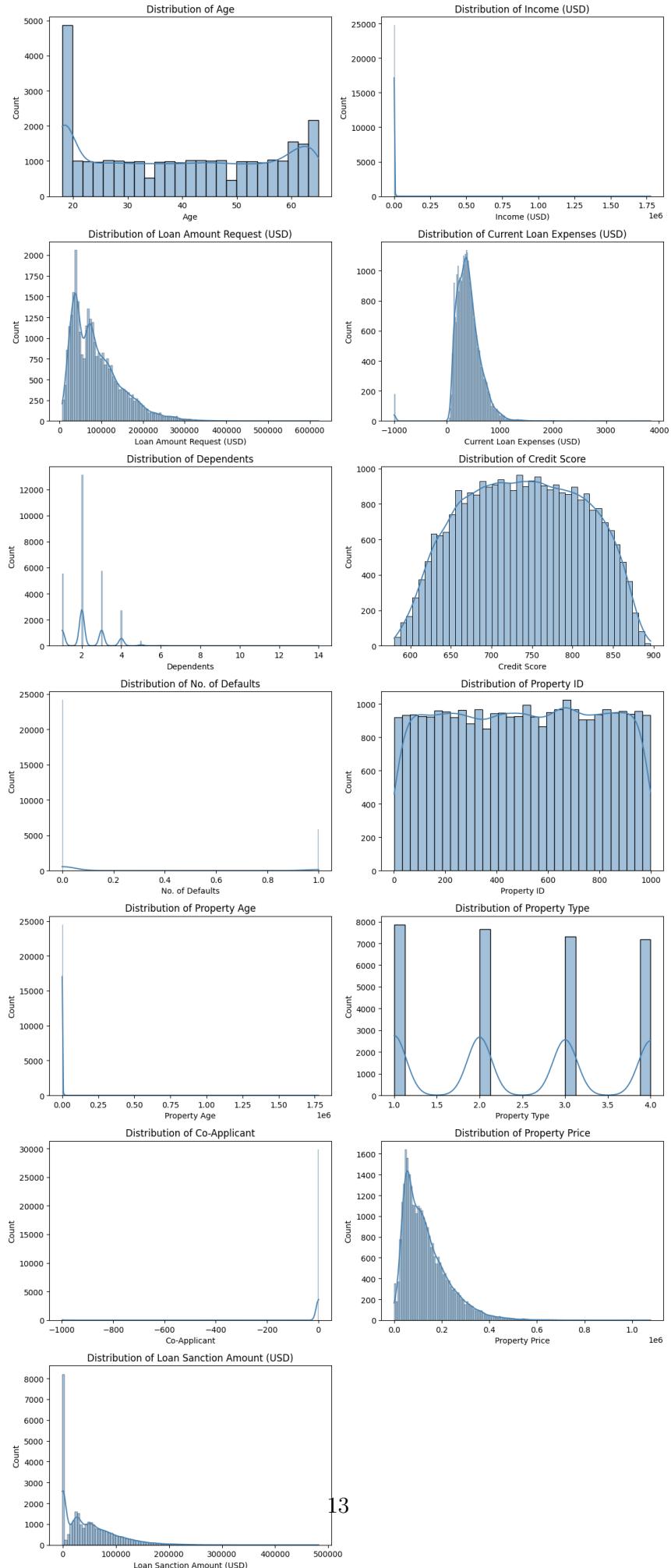
```
n_rows = int(np.ceil(len(numeric_cols) / n_cols))

fig, axes = plt.subplots(n_rows, n_cols, figsize=(12, 4 * n_rows))
axes = axes.flatten()

for i, col in enumerate(numeric_cols):
    sns.histplot(df[col], kde=True, ax=axes[i], color="steelblue")
    axes[i].set_title(f"Distribution of {col}")

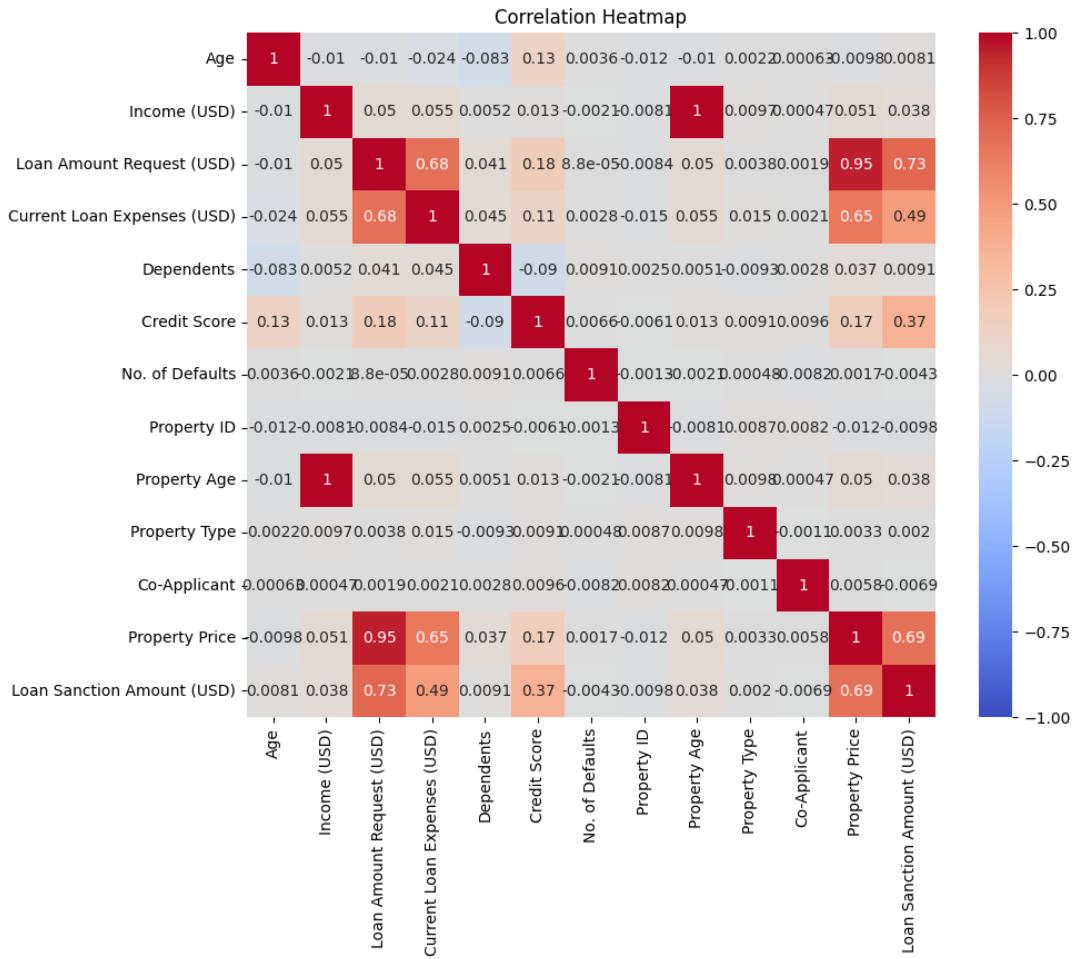
# Remove empty subplots (if any)
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.show()
```



```
[6]: if "Loan_Status" in df.columns:  
    plt.figure(figsize=(12, 8))  
  
    melted = df.melt(  
        id_vars="Loan_Status",  
        value_vars=numeric_cols,  
        var_name="Feature",  
        value_name="Value"  
    )  
  
    sns.boxplot(data=melted, x="Feature", y="Value", hue="Loan_Status")  
    plt.title("Feature distributions by Loan Status")  
    plt.xticks(rotation=45)  
    plt.show()
```

```
[7]: plt.figure(figsize=(10, 8))  
  
corr = df[numeric_cols].corr()  
sns.heatmap(corr, annot=True, cmap="coolwarm", vmin=-1, vmax=1)  
plt.title("Correlation Heatmap")  
plt.show()
```



#DIABETES DATASET

```
[8]: df = pd.read_csv("diabetes.csv")
df.head()
```

```
[8]:    Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin  BMI \
0            6      148                  72                 35        0   33.6
1            1       85                  66                 29        0   26.6
2            8      183                  64                  0        0   23.3
3            1       89                  66                 23        94  28.1
4            0      137                  40                 35       168  43.1
```

	DiabetesPedigreeFunction	Age	Outcome
0	0.627	50	1
1	0.351	31	0
2	0.672	32	1
3	0.167	21	0
4	2.288	33	1

```
[9]: print("Shape:", df.shape)

print("\nInfo:")
df.info()

print("\nMissing values per column:")
print(df.isnull().sum())
```

Shape: (768, 9)

Info:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype  
---  --  
 0   Pregnancies      768 non-null    int64  
 1   Glucose          768 non-null    int64  
 2   BloodPressure    768 non-null    int64  
 3   SkinThickness    768 non-null    int64  
 4   Insulin          768 non-null    int64  
 5   BMI              768 non-null    float64 
 6   DiabetesPedigreeFunction 768 non-null    float64 
 7   Age              768 non-null    int64  
 8   Outcome          768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

Missing values per column:

Pregnancies	0
Glucose	0
BloodPressure	0
SkinThickness	0
Insulin	0
BMI	0
DiabetesPedigreeFunction	0
Age	0
Outcome	0

dtype: int64

```
[10]: df.describe(include="all")
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	\
count	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	120.894531	69.105469	20.536458	79.799479	

std	3.369578	31.972618	19.355807	15.952218	115.244002
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000
75%	6.000000	140.250000	80.000000	32.000000	127.250000
max	17.000000	199.000000	122.000000	99.000000	846.000000

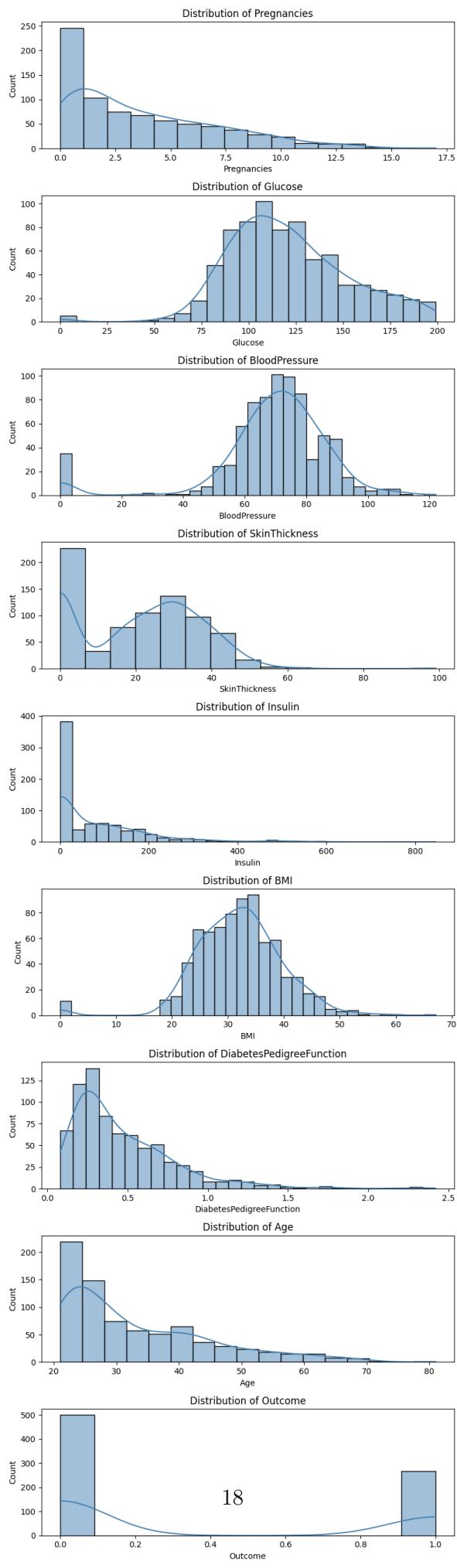
	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000
mean	31.992578	0.471876	33.240885	0.348958
std	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.078000	21.000000	0.000000
25%	27.300000	0.243750	24.000000	0.000000
50%	32.000000	0.372500	29.000000	0.000000
75%	36.600000	0.626250	41.000000	1.000000
max	67.100000	2.420000	81.000000	1.000000

```
[11]: numeric_cols = df.select_dtypes(include=["int64", "float64"]).columns

fig, axes = plt.subplots(len(numeric_cols), 1, figsize=(8, 1
→3*len(numeric_cols)))

for i, col in enumerate(numeric_cols):
    sns.histplot(df[col], kde=True, ax=axes[i], color="steelblue")
    axes[i].set_title(f"Distribution of {col}")

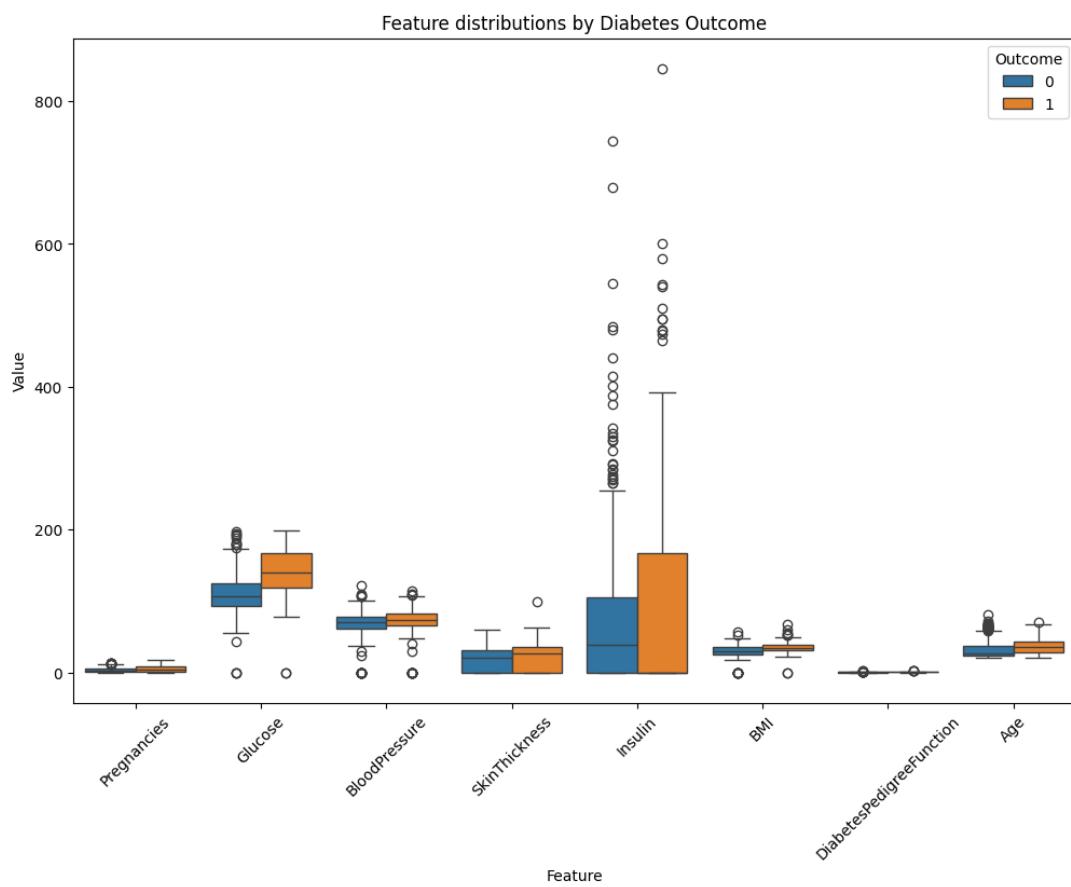
plt.tight_layout()
plt.show()
```



```
[12]: if "Outcome" in df.columns:
    plt.figure(figsize=(12, 8))

    melted = df.melt(
        id_vars="Outcome",
        value_vars=numeric_cols,
        var_name="Feature",
        value_name="Value"
    )

    sns.boxplot(data=melted, x="Feature", y="Value", hue="Outcome")
    plt.title("Feature distributions by Diabetes Outcome")
    plt.xticks(rotation=45)
    plt.show()
```



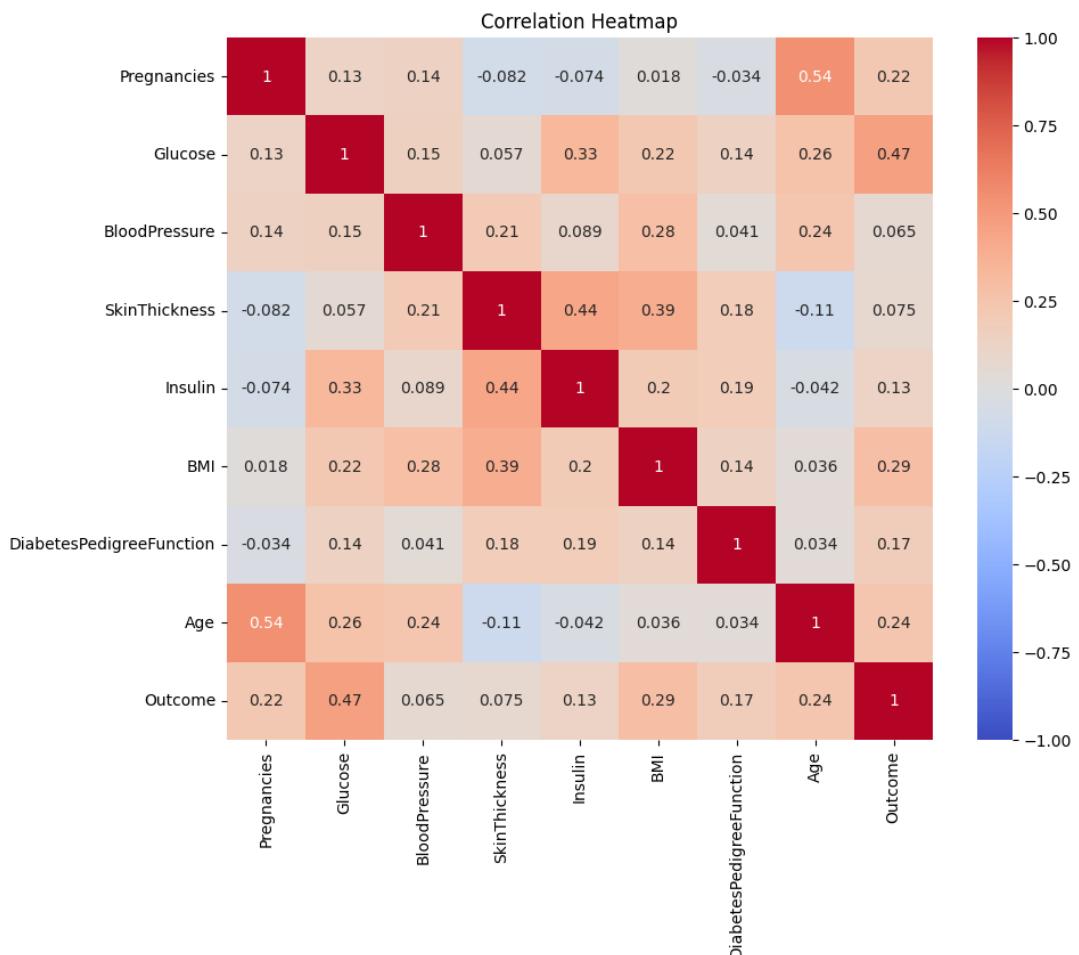
```
[13]: plt.figure(figsize=(10, 8))
```

```

corr = df[numerical_cols].corr()
sns.heatmap(corr, annot=True, cmap="coolwarm", vmin=-1, vmax=1)

plt.title("Correlation Heatmap")
plt.show()

```



```

[14]: categorical_cols = df.select_dtypes(include=["object"]).columns

for col in categorical_cols:
    plt.figure(figsize=(6, 4))
    sns.countplot(data=df, x=col, hue="Outcome" if "Outcome" in df.columns
    ↪ else None)
    plt.title(f"Counts of {col}")
    plt.xticks(rotation=45)
    plt.show()

```

#EMAIL CLASSIFICATION

```
[15]: df = pd.read_csv("email.csv")
df.head()
```

```
[15]:   Category                         Message
0      ham  Go until jurong point, crazy.. Available only ...
1      ham                  Ok lar... Joking wif u oni...
2     spam  Free entry in 2 a wkly comp to win FA Cup fina...
3      ham  U dun say so early hor... U c already then say...
4      ham  Nah I don't think he goes to usf, he lives aro...
```

```
[16]: print("Shape:", df.shape)
df.info()
```

```
print("\nMissing values:")
print(df.isnull().sum())
```

```
Shape: (5572, 2)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5572 entries, 0 to 5571
Data columns (total 2 columns):
 #   Column    Non-Null Count  Dtype  
---  --  
 0   Category   5572 non-null   object 
 1   Message    5572 non-null   object 
dtypes: object(2)
memory usage: 87.2+ KB
```

```
Missing values:
Category      0
Message       0
dtype: int64
```

```
[17]: df.describe(include="all")
```

```
[17]:   Category                         Message
count      5572                          5572
unique      2                           5157
top        ham  Sorry, I'll call later
freq      4825                          30
```

```
[18]: numeric_cols = df.select_dtypes(include=["int64", "float64"]).columns
```

```
if len(numeric_cols) > 0:
    rows = math.ceil(len(numeric_cols)/2)
    fig, axes = plt.subplots(rows, 2, figsize=(12, 4*rows))
    axes = axes.ravel()
```

```

for i, col in enumerate(numeric_cols):
    sns.histplot(df[col], kde=True, ax=axes[i], color="steelblue")
    axes[i].set_title(f"Distribution of {col}")

for j in range(i+1, len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.show()

```

```
[19]: if len(numeric_cols) > 0:
    plt.figure(figsize=(10, 8))
    corr = df[numeric_cols].corr()
    sns.heatmap(corr, annot=True, cmap="coolwarm", vmin=-1, vmax=1)
    plt.title("Correlation Heatmap")
    plt.show()
```

#HANDWRITING RECOGNITION

```
[22]: df = pd.read_csv("english.csv")
df.head()
```

```
[22]:      image  label
0  Img/img001-001.png    0
1  Img/img001-002.png    0
2  Img/img001-003.png    0
3  Img/img001-004.png    0
4  Img/img001-005.png    0
```

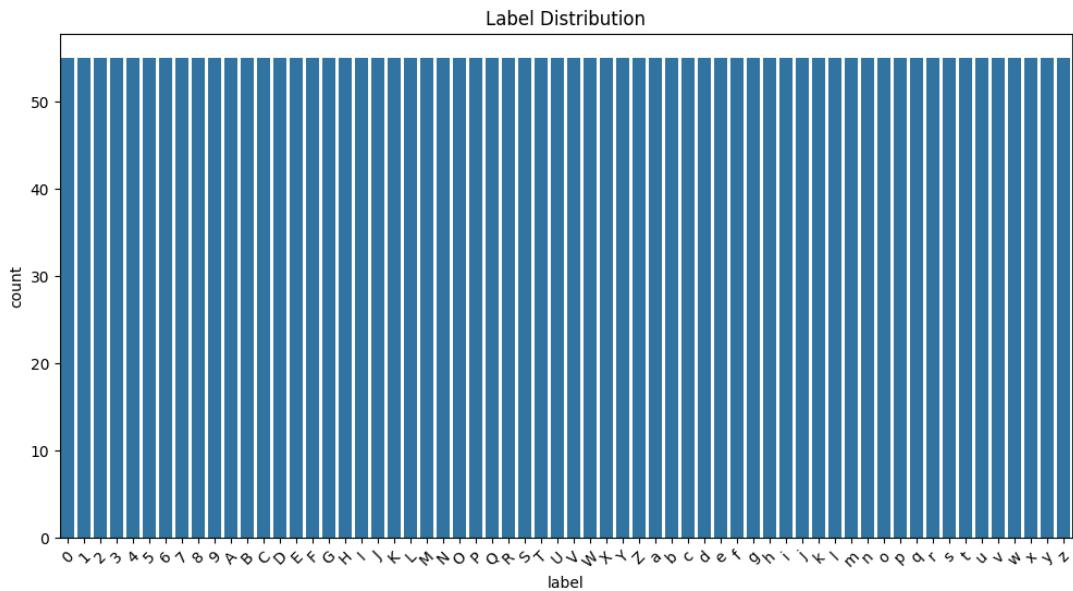
```
[23]: print("Shape:", df.shape)
df.info()

print("\nMissing values:")
print(df.isnull().sum())
```

```
Shape: (3410, 2)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3410 entries, 0 to 3409
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  -- 
 0   image    3410 non-null   object 
 1   label    3410 non-null   object 
dtypes: object(2)
memory usage: 53.4+ KB
```

```
Missing values:  
image      0  
label      0  
dtype: int64
```

```
[24]: plt.figure(figsize=(12, 6))  
sns.countplot(data=df, x="label", order=df["label"].value_counts().index)  
plt.title("Label Distribution")  
plt.xticks(rotation=45)  
plt.show()
```



```
[25]: def show_samples(df, labels, samples_per_label=5):  
    fig, axes = plt.subplots(  
        len(labels), samples_per_label,  
        figsize=(samples_per_label*2, len(labels)*2)  
    )  
  
    for i, label in enumerate(labels):  
        subset = df[df["label"] == label].sample(samples_per_label,   
→random_state=42)  
        for j, img_path in enumerate(subset["image"].values):  
            path = "handwritten/" + img_path  
            if os.path.exists(path):  
                img = cv2.imread(path, cv2.IMREAD_GRAYSCALE)  
                axes[i, j].imshow(img, cmap="gray")  
                axes[i, j].axis("off")
```

```

        axes[i, j].set_title(str(label))
    else:
        axes[i, j].text(0.5, 0.5, "Missing", ha="center", va="center")
        axes[i, j].axis("off")

plt.tight_layout()
plt.show()

```

[26]: unique\_labels = df["label"].unique()  
show\_samples(df, unique\_labels[:5], samples\_per\_label=5)

Missing Missing Missing Missing Missing

[29]: heights, widths = [], []

for img\_path in df["image"].sample(min(200, len(df)), random\_state=42):
 path = "handwritten/" + img\_path

```

if os.path.exists(path):
    img = cv2.imread(path)
    if img is not None:
        h, w = img.shape[:2]
        heights.append(h)
        widths.append(w)

plt.figure(figsize=(10, 5))

ax = sns.histplot(heights, kde=True, color="steelblue", label="Heights")
sns.histplot(widths, kde=True, color="orange", label="Widths", ax=ax)

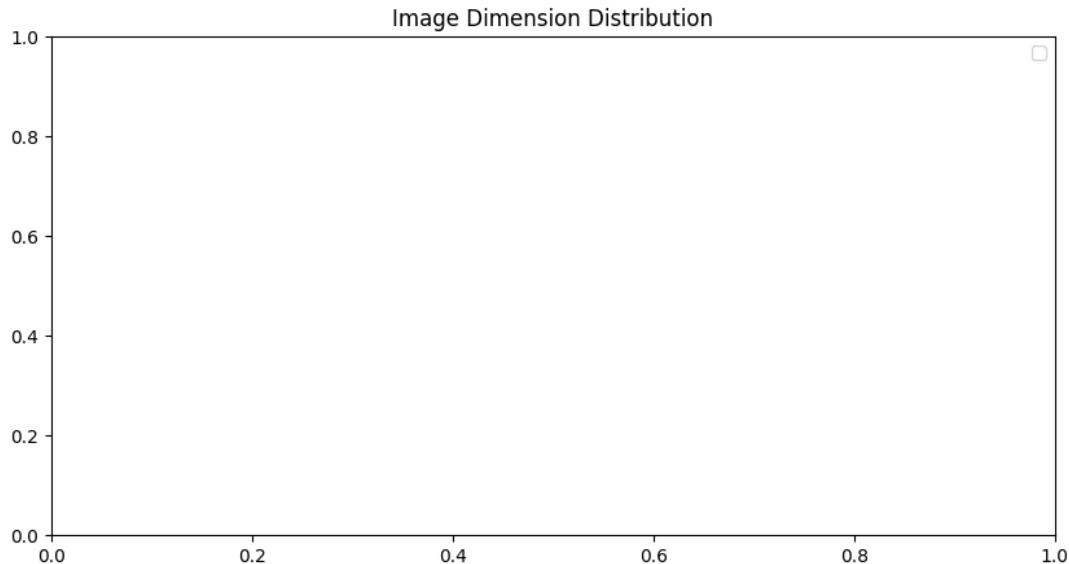
ax.legend()
ax.set_title("Image Dimension Distribution")

plt.show()

```

C:\Users\Sabarithan P\AppData\Local\Temp\ipykernel\_1392\2171688439.py:17:  
UserWarning: No artists with labels found to put in legend. Note that artists  
whose label start with an underscore are ignored when legend() is called with no  
argument.

```
ax.legend()
```



[ ]: