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

Degree & Branch	B.E. Computer Science & Engineering	Semester	VI
Subject Code & Name	UCS2612 & Machine Learning Laboratory		
Academic year	2025-2026 (Even)	Batch:2023-2027	**Due date: 27-01-2026**

Experiment 1 : Working with python packages-Numpy, Scipy, Scikit-learn, Matplotlib

Aim: To study and explore the python library such as Pandas, Numpy, matplotlib, Scikit-learn, and Scipy to understand the data science and machine learning and understand how the different datasets are analyzed, and mapped to different machine learning models using exploratory data analysis technique.

Libraries used:

- **NumPy:** Used for numerical computations and efficient handling of multi-dimensional arrays.
- **Pandas:** Used for data manipulation, cleaning, and analysis using DataFrames.
- **Matplotlib:** Used for creating visualizations such as line graphs, bar charts, and histograms.
- **Seaborn:** Used for advanced statistical data visualization with attractive and informative plots.
- **Scikit-learn:** Used for implementing machine learning algorithms, model training, evaluation, preprocessing, and feature selection.
- **SciPy:** Used for scientific and technical computing, including optimization, and statistical functions.

0.0.1 Loan Amount Prediction

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

df = pd.read_csv("dataset/loan_train.csv")
df
```

[1]:
```
      Customer ID              Name Gender  Age  Income (USD)  \
0         C-36995   Frederica Shealy      F   56       1933.05
1         C-33999  America Calderone      M   32       4952.91
2          C-3770      Rosetta Verne      F   65        988.19
3         C-26480         Zoe Chitty      F   65           NaN
4         C-23459       Afton Venema      F   31       2614.77
...           ...                ...    ...  ...           ...
29995     C-43723  Angelyn Clevenger      M   38       4969.41
29996     C-32511       Silas Slaugh      M   20       1606.88
```

```
29997      C-5192       Carmelo Lone      F   49           NaN
29998     C-12172      Carolann Osby      M   38       2417.71
29999     C-33003  Bridget Garibaldi      F   63       3068.24

      Income Stability            Profession     Type of Employment  \
0                  Low               Working            Sales staff
1                  Low               Working                    NaN
2                 High             Pensioner                    NaN
3                 High             Pensioner                    NaN
4                  Low               Working  High skill tech staff
...                ...                   ...                    ...
29995              Low  Commercial associate               Managers
29996              Low               Working               Laborers
29997              Low               Working            Sales staff
29998              Low               Working         Security staff
29999             High             Pensioner                    NaN

         Location  Loan Amount Request (USD)  ...  Credit Score  \
0      Semi-Urban                   72809.58  ...        809.44
1      Semi-Urban                   46837.47  ...        780.40
2      Semi-Urban                   45593.04  ...        833.15
3           Rural                   80057.92  ...        832.70
4      Semi-Urban                  113858.89  ...        745.55
...           ...                        ...  ...           ...
29995       Urban                   76657.90  ...        869.61
29996  Semi-Urban                   66595.14  ...        729.41
29997       Urban                   81410.08  ...           NaN
29998  Semi-Urban                  142524.10  ...        677.27
29999       Rural                  156290.54  ...        815.44

      No. of Defaults Has Active Credit Card  Property ID  Property Age  \
0                   0                    NaN         746       1933.05
1                   0             Unpossessed         608       4952.91
2                   0             Unpossessed         546        988.19
3                   1             Unpossessed         890           NaN
4                   1                  Active         715       2614.77
...               ...                     ...         ...           ...
29995               0             Unpossessed         566       4969.41
29996               0                Inactive         175       1606.88
29997               0                  Active         959           NaN
29998               1             Unpossessed         375       2417.71
29999               0                  Active         344       3068.24

       Property Type Property Location  Co-Applicant  Property Price  \
0                  4             Rural             1       119933.46
1                  2             Rural             1        54791.00
2                  2             Urban             0        72440.58
```

```
3                   2        Semi-Urban             1       121441.51
4                   4        Semi-Urban             1       208567.91
...               ...               ...           ...             ...
29995               4             Urban             1       111096.56
29996               3             Urban             1        73453.94
29997               1             Rural             1       102108.02
29998               4             Urban             1       168194.47
29999               3             Rural             1       194512.60

       Loan Sanction Amount (USD)
0                        54607.18
1                        37469.98
2                        36474.43
3                        56040.54
4                        74008.28
...                           ...
29995                    68992.11
29996                    46616.60
29997                    61057.56
29998                    99766.87
29999                   117217.90

[30000 rows x 24 columns]
```

[2]:
```
print("Info \n", df.info())
df.describe().T
```

```
<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
Info
 None
```

[2]:

	count	mean	std	min
Age	30000.0	40.092300	16.045129	18.00
Income (USD)	25424.0	2630.574417	11262.723830	377.70
Loan Amount Request (USD)	30000.0	88826.333855	59536.949605	6048.24
Current Loan Expenses (USD)	29828.0	400.936876	242.545375	-999.00
Dependents	27507.0	2.253027	0.951162	1.00
Credit Score	28297.0	739.885381	72.163846	580.00
No. of Defaults	30000.0	0.193933	0.395384	0.00
Property ID	30000.0	501.934700	288.158086	1.00
Property Age	25150.0	2631.119440	11322.677000	377.70
Property Type	30000.0	2.460067	1.118562	1.00
Co-Applicant	30000.0	-4.743867	74.614593	-999.00
Property Price	30000.0	131759.680252	93549.548104	-999.00
Loan Sanction Amount (USD)	29660.0	47649.342208	48221.146686	-999.00

	25%	50%	75%	max
Age	25.0000	40.000	55.0000	65.00
Income (USD)	1650.4575	2222.435	3090.5925	1777460.21
Loan Amount Request (USD)	41177.7550	75128.075	119964.6050	621497.82
Current Loan Expenses (USD)	247.6675	375.205	521.2925	3840.88
Dependents	2.0000	2.000	3.0000	14.00
Credit Score	681.8800	739.820	799.1200	896.26
No. of Defaults	0.0000	0.000	0.0000	1.00
Property ID	251.0000	504.000	751.0000	999.00
Property Age	1650.4500	2223.250	3091.4075	1777460.21
Property Type	1.0000	2.000	3.0000	4.00
Co-Applicant	1.0000	1.000	1.0000	1.00
Property Price	60572.1600	109993.610	178880.7200	1077966.73
Loan Sanction Amount (USD)	0.0000	35209.395	74261.2500	481907.32

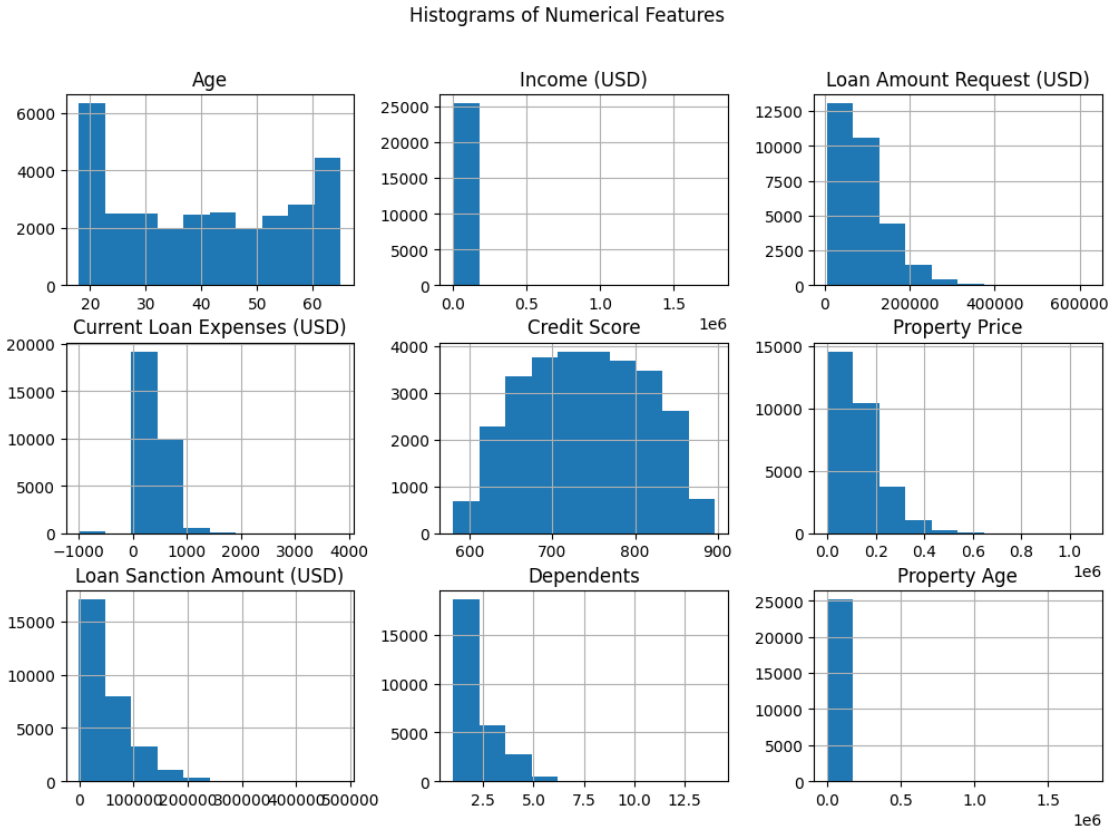
[3]:
```
df.isnull().sum()
```

[3]:
```
Customer ID                    0
Name                           0
Gender                        53
```

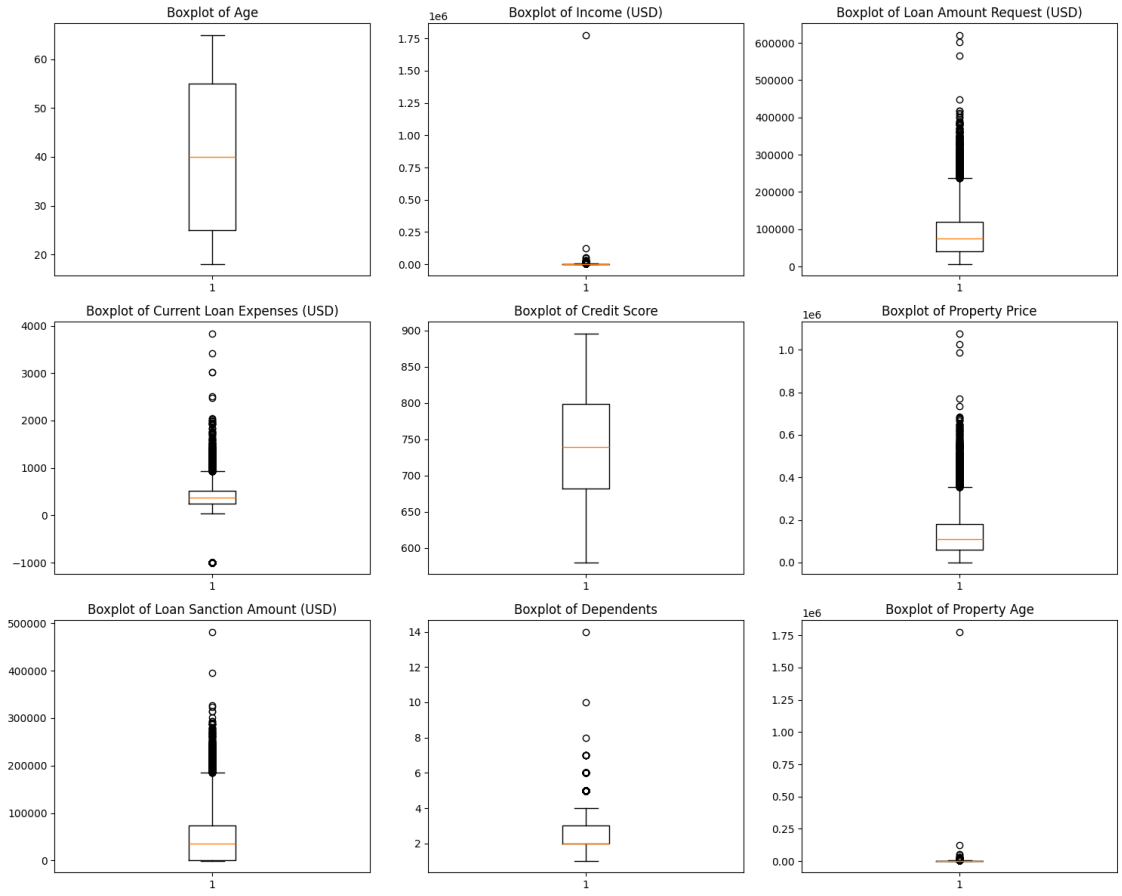
```
Age                                0
Income (USD)                    4576
Income Stability                1683
Profession                         0
Type of Employment              7270
Location                           0
Loan Amount Request (USD)          0
Current Loan Expenses (USD)      172
Expense 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
```

Exploratory Data Analysis

[4]:
```
numcols = ['Age', 'Income (USD)', 'Loan Amount Request (USD)',
'Current Loan Expenses (USD)', 'Credit Score',
'Property Price', 'Loan Sanction Amount (USD)','Dependents','Property Age']

df[numcols].hist(figsize=(12,8))
plt.suptitle("Histograms of Numerical Features")
plt.show()
```



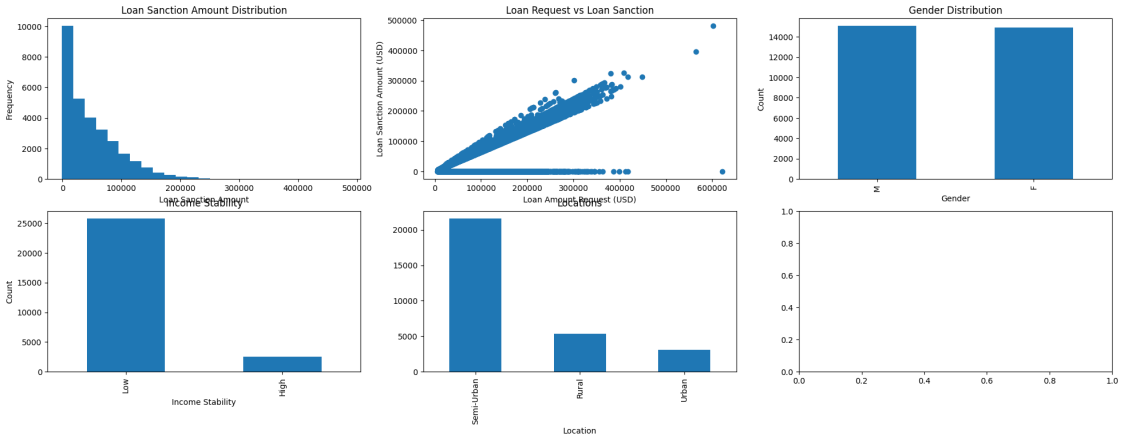
[5]:
```
import matplotlib.pyplot as plt

num_cols = [
    'Age', 'Income (USD)', 'Loan Amount Request (USD)',
    'Current Loan Expenses (USD)', 'Credit Score',
    'Property Price', 'Loan Sanction Amount (USD)',
    'Dependents','Property Age'
]

fig, axes = plt.subplots(3, 3, figsize=(15, 12))  # 3x3 grid
axes = axes.flatten()  # flatten to easily loop

for ax, col in zip(axes, num_cols):
    ax.boxplot(df[col].dropna())
    ax.set_title(f"Boxplot of {col}")

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



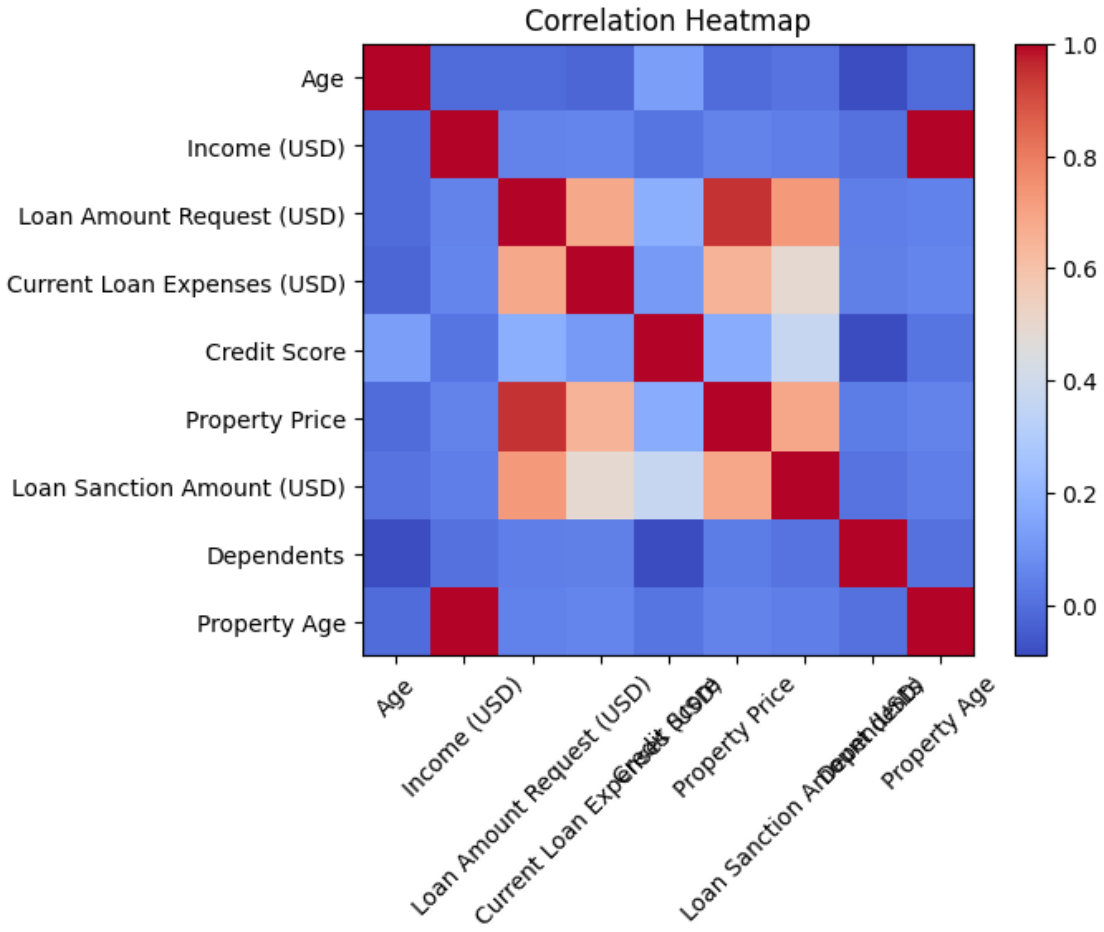
[6]:
```
fig, axes = plt.subplots(2, 3, figsize=(24, 8))
axes = axes.flatten()
# Histogram
axes[0].hist(df["Loan Sanction Amount (USD)"], bins=25)
axes[0].set_title("Loan Sanction Amount Distribution")
axes[0].set_xlabel("Loan Sanction Amount")
axes[0].set_ylabel("Frequency")

axes[1].scatter(df["Loan Amount Request (USD)"], df["Loan Sanction Amount␣
 ↪(USD)"])
axes[1].set_xlabel("Loan Amount Request (USD)")
axes[1].set_ylabel("Loan Sanction Amount (USD)")
axes[1].set_title("Loan Request vs Loan Sanction")

df["Gender"].value_counts().plot(kind = 'bar', ax = axes[2])
axes[2].set_title("Gender Distribution")
axes[2].set_xlabel("Gender")
axes[2].set_ylabel("Count")
```

```
df["Income Stability"].value_counts().plot(kind = 'bar', ax = axes[3])
axes[3].set_title("Income Stability")
axes[3].set_xlabel("Income Stability")
axes[3].set_ylabel("Count")

df["Location"].value_counts().plot(kind = 'bar', ax = axes[4])
axes[4].set_title("Locations")
axes[3].set_ylabel("Count")
```

[6]: Text(0, 0.5, 'Count')



[7]:
```
corr = df[numcols].corr()
plt.imshow(corr, cmap='coolwarm')
plt.colorbar()
plt.xticks(range(len(corr.columns)), corr.columns, rotation=45)
plt.yticks(range(len(corr.columns)), corr.columns)
plt.title("Correlation Heatmap")
plt.show()
```



0.0.2 Iris

[8]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

df=pd.read_csv('dataset/Iris.csv')
df.head()
```

[8]:

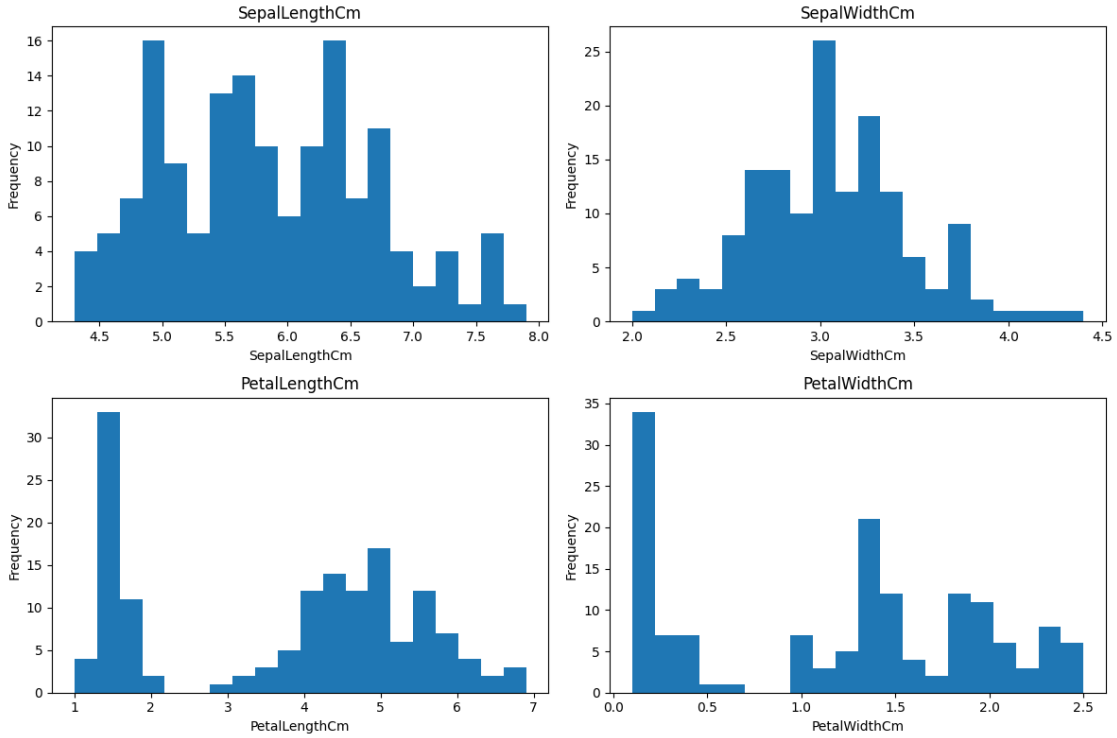
	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

[9]:
```
df.describe().T
```

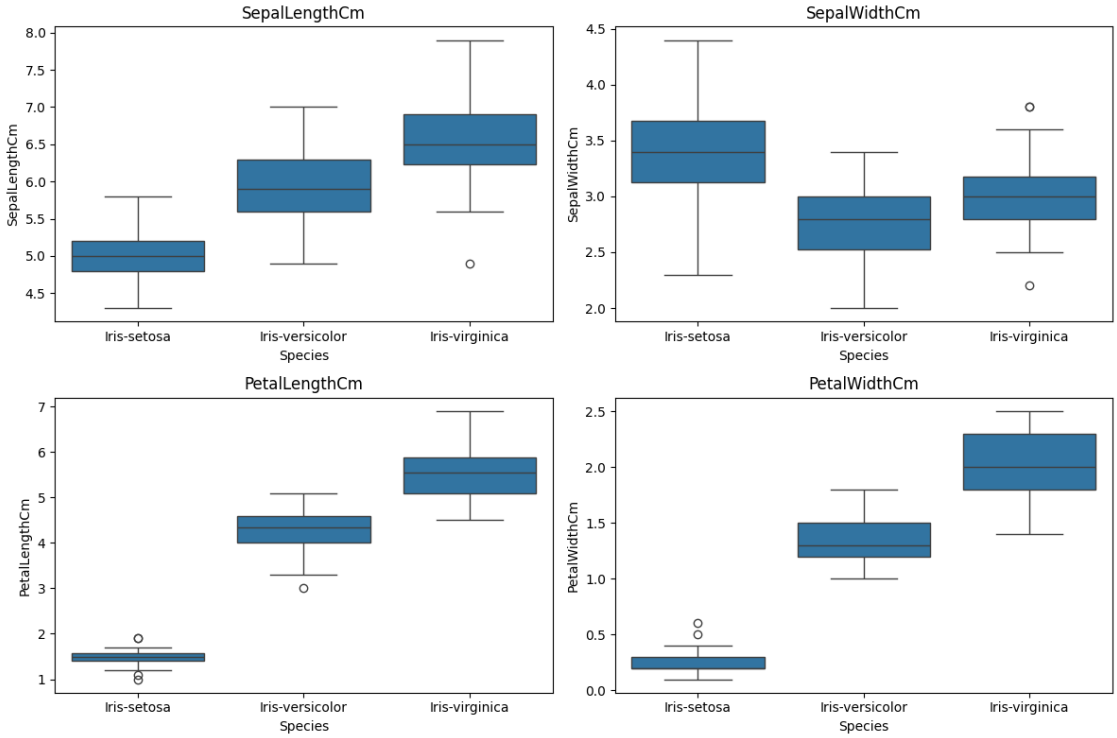
[9]:

	count	mean	std	min	25%	50%	75%	max
Id	150.0	75.500000	43.445368	1.0	38.25	75.50	112.75	150.0
SepalLengthCm	150.0	5.843333	0.828066	4.3	5.10	5.80	6.40	7.9
SepalWidthCm	150.0	3.054000	0.433594	2.0	2.80	3.00	3.30	4.4
PetalLengthCm	150.0	3.758667	1.764420	1.0	1.60	4.35	5.10	6.9
PetalWidthCm	150.0	1.198667	0.763161	0.1	0.30	1.30	1.80	2.5

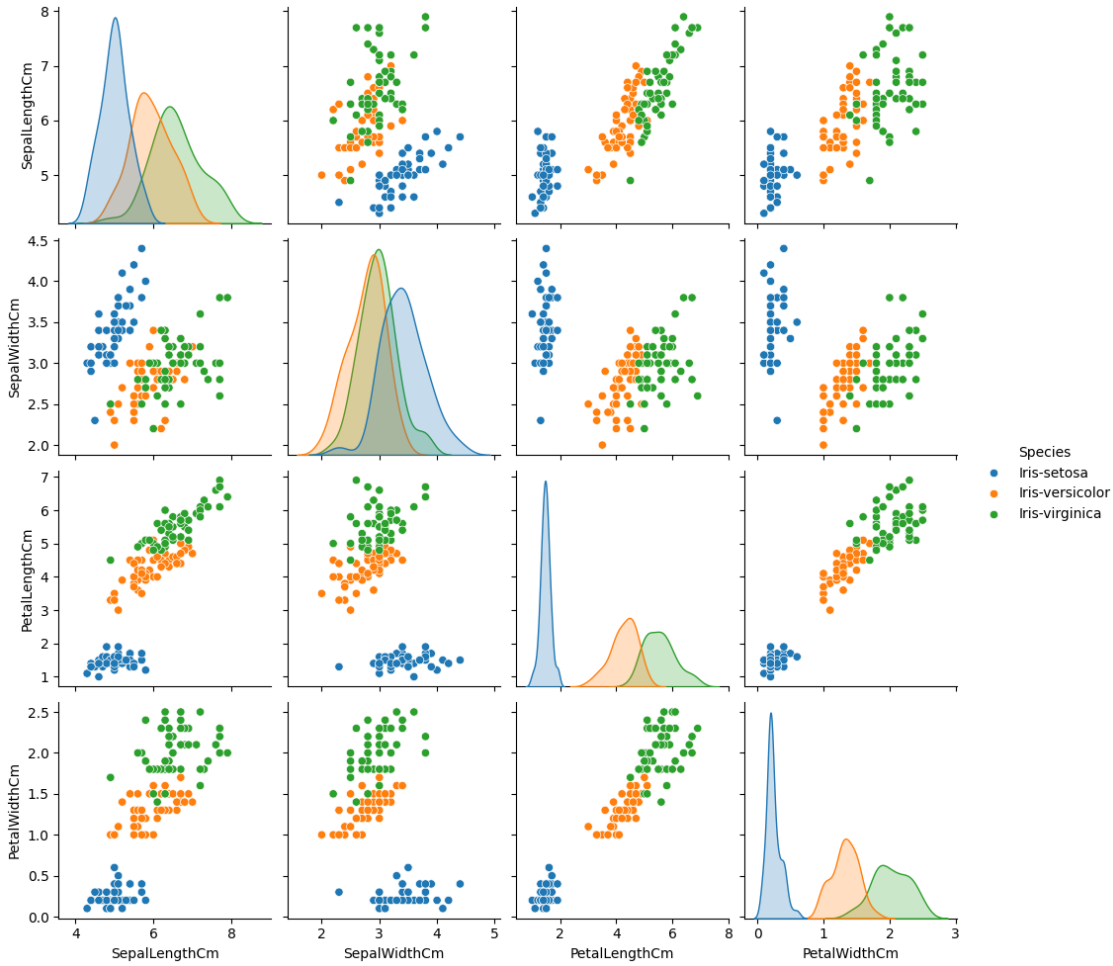
[10]:
```
features = [
    'SepalLengthCm',
    'SepalWidthCm',
    'PetalLengthCm',
    'PetalWidthCm'
]

plt.figure(figsize=(12, 8))

for i, col in enumerate(features, 1):
    plt.subplot(2, 2, i)
    plt.hist(df[col], bins=20)
    plt.title(col)
    plt.xlabel(col)
    plt.ylabel('Frequency')

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



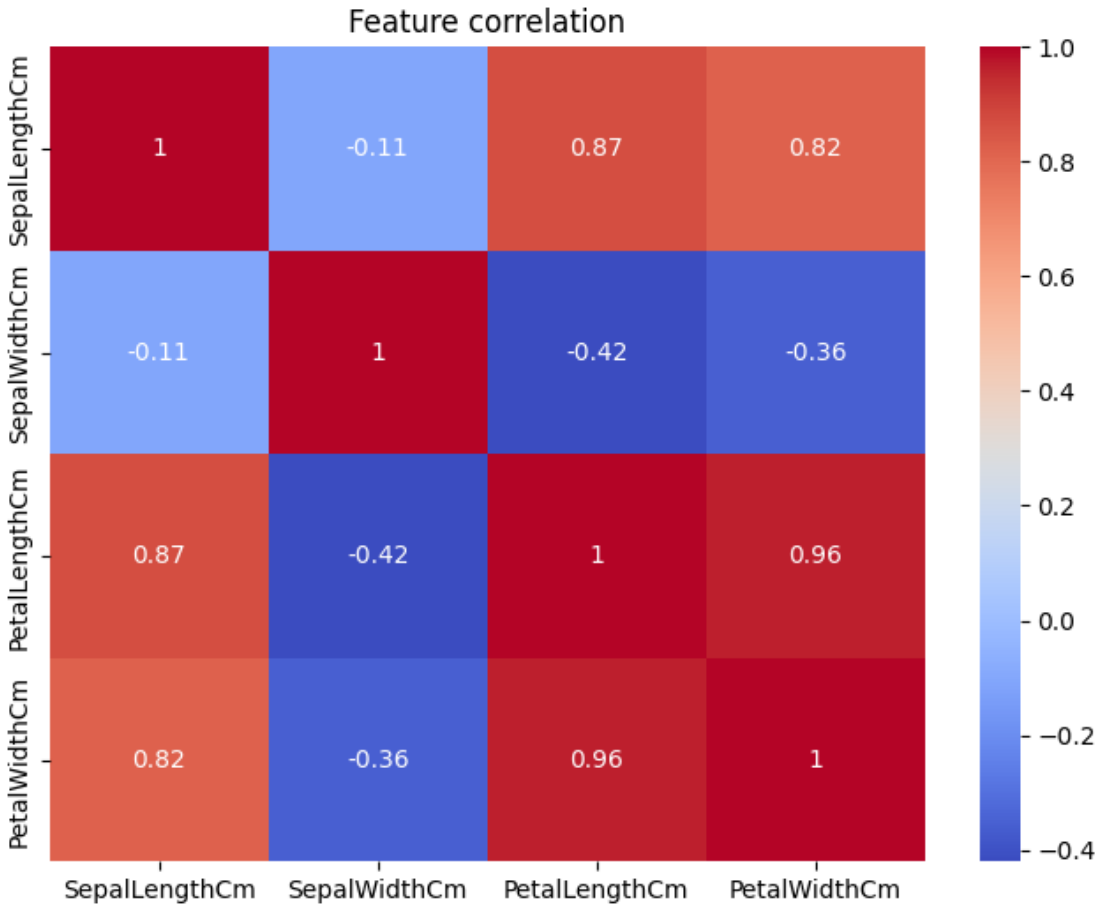
[11]:
```
plt.figure(figsize=(12, 8))

for i, col in enumerate(features, 1):
    plt.subplot(2, 2, i)
    sns.boxplot(x='Species', y=col, data=df)
    plt.title(col)

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



[12]:
```
sns.pairplot(df.drop('Id', axis = 1), hue='Species')
plt.show()
```



[13]:
```
plt.figure(figsize=(8,6))
sns.heatmap(df.drop(['Species', 'Id'], axis=1).corr(),
            annot=True, cmap='coolwarm')
plt.title("Feature correlation")
plt.show()
```



0.0.3 Hand Written Character Recognition

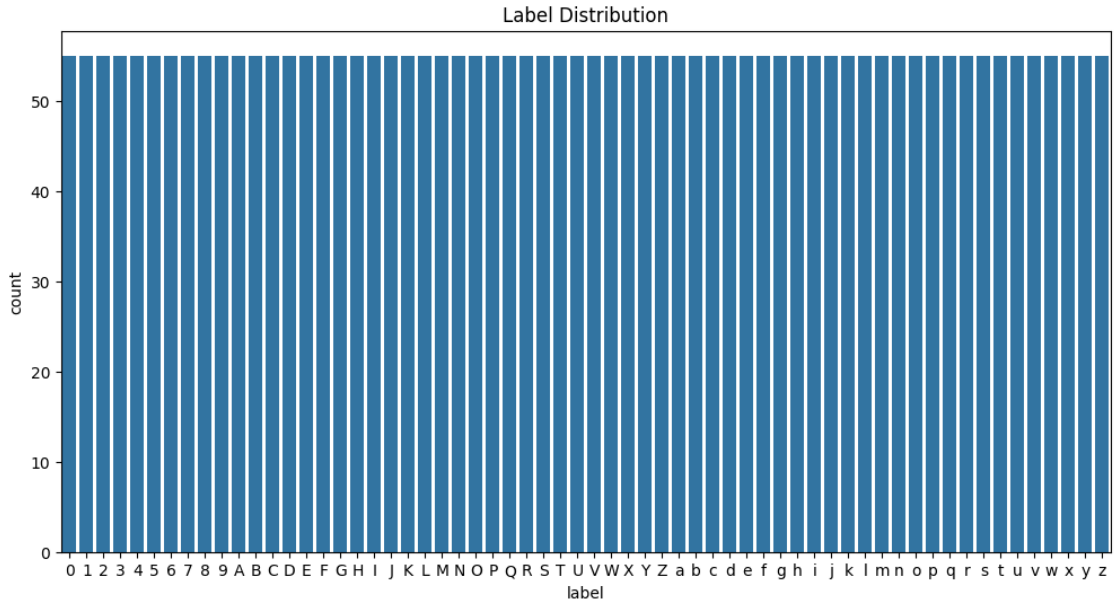
[45]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
import math

df = pd.read_csv("datasets/english.csv")
```

[46]:
```
print("Shape:", df.shape)
print("Info\n",df.info())
print("Head\n",df.head())

print(df.isnull().sum())
```

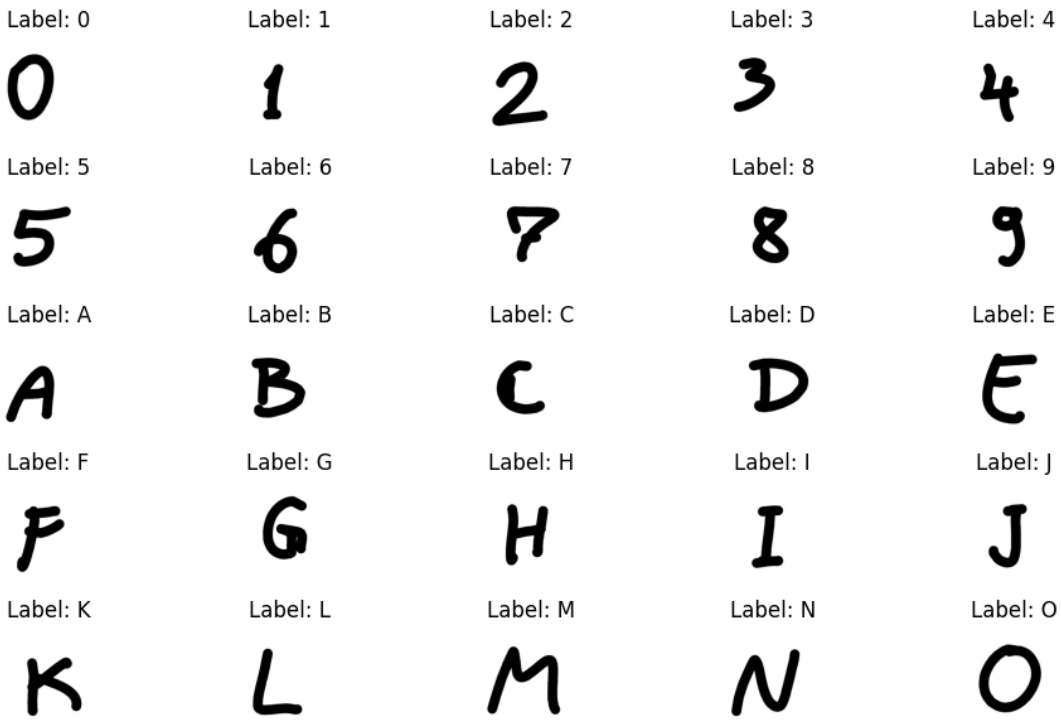
```
Shape: (3410, 2)
<class 'pandas.core.frame.DataFrame'>
```

```
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
Info
 None
Head
                  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
image    0
label    0
dtype: int64
```

[47]:
```
plt.figure(figsize=(12,6))
sns.countplot(data=df, x="label", order=df["label"].value_counts().index)
plt.title("Label Distribution")
plt.show()
```

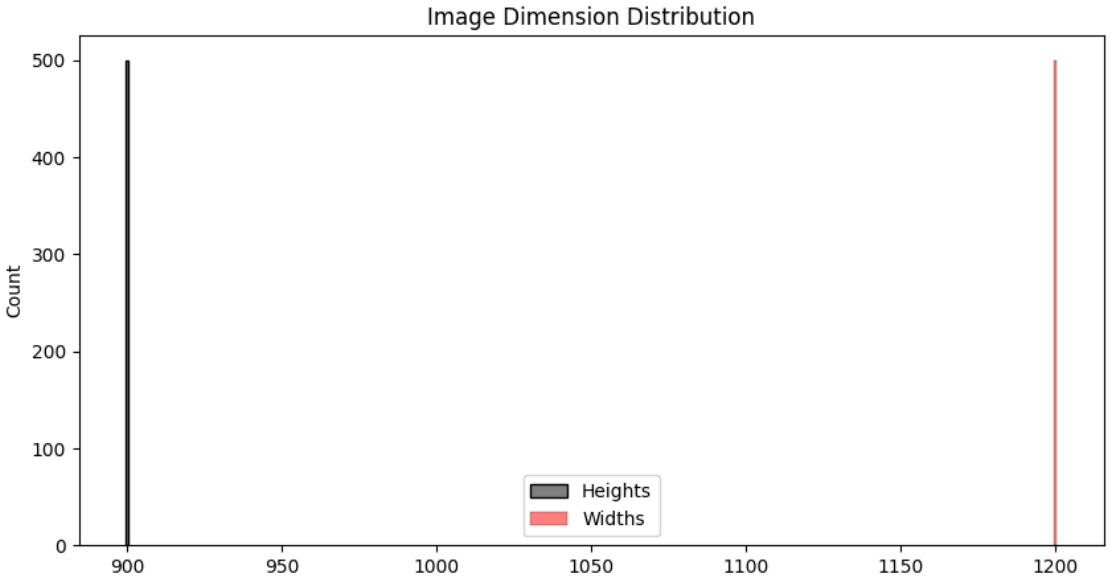


[48]:
```
from PIL import Image

plt.figure(figsize=(10, 6))

unique = df.groupby('label').first().reset_index().head(25)

for i, row in unique.iterrows():
    img_path = row['image']
    label = row['label']

    img = Image.open(f"datasets/{img_path}")

    plt.subplot(5, 5, i+1)
    plt.imshow(img, cmap='gray')
    plt.title(f"Label: {label}")
    plt.axis('off')

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



[49]:
```
from PIL import Image

heights = []
```

```
widths = []

for img_path in df['image'][:500]:
    img = Image.open(f"datasets/{img_path}")
    w, h = img.size
    widths.append(w)
    heights.append(h)


plt.figure(figsize=(10,5))
sns.histplot(heights, kde=True, color="black", label="Heights")
sns.histplot(widths, kde=True, color="red", label="Widths")
plt.legend()
plt.title("Image Dimension Distribution")
plt.show()
```



[14]:
```
import pandas as pd

df = pd.read_csv("dataset/diabetes.csv")
```

[17]:
```
print("Shape:", df.shape)
print("Info\n", df.info())
df.head()
```

```
Shape: (768, 9)
<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
Info
 None
```

[17]:

	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

[18]:
```
df.isnull().sum()
```

[18]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

[19]:
```
df.describe().T
```

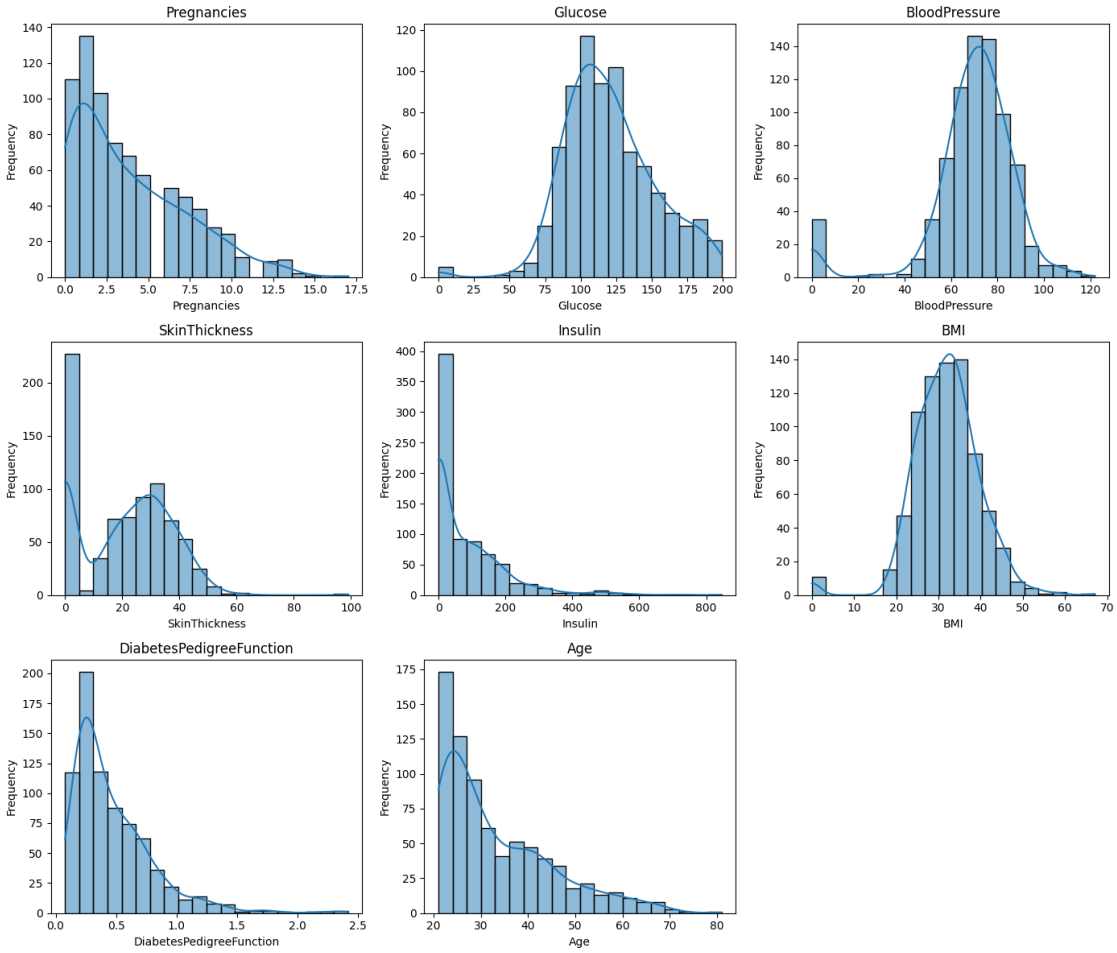
[19]:

	count	mean	std	min	25%	\
Pregnancies	768.0	3.845052	3.369578	0.000	1.00000	
Glucose	768.0	120.894531	31.972618	0.000	99.00000	

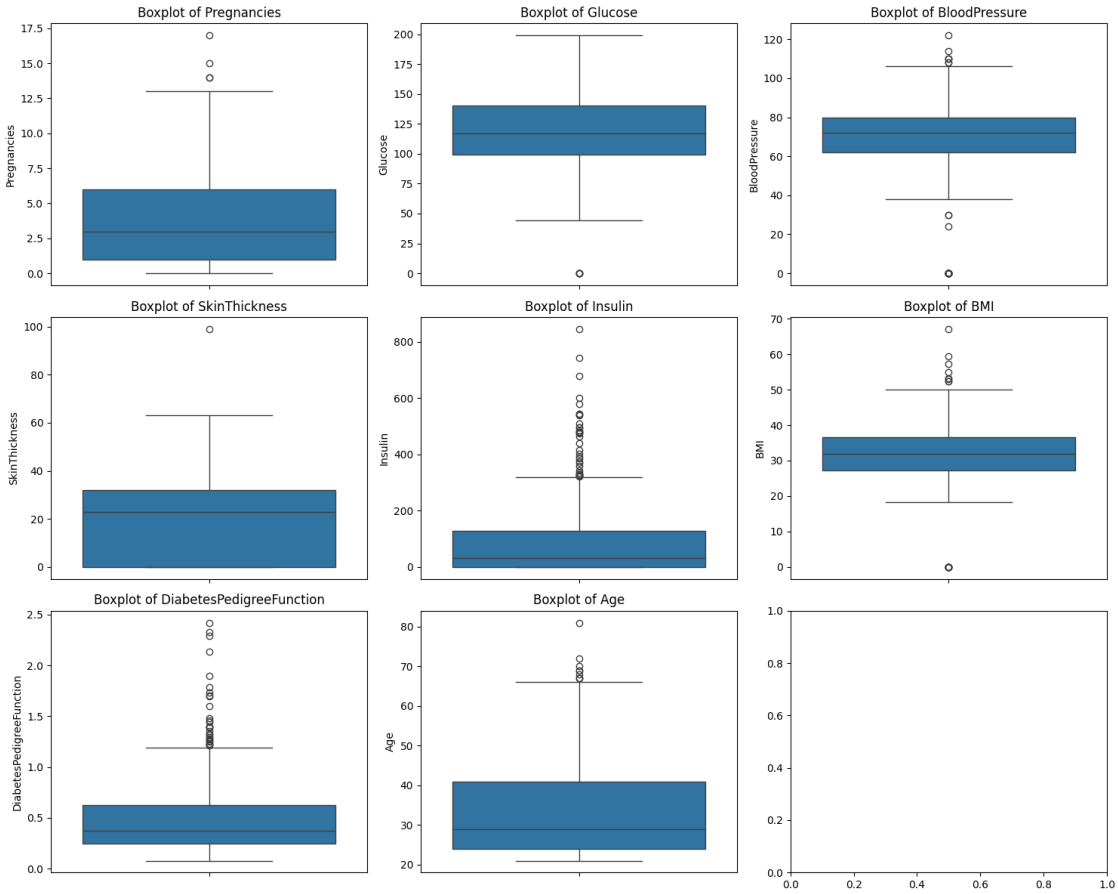
BloodPressure	768.0	69.105469	19.355807	0.000	62.00000
SkinThickness	768.0	20.536458	15.952218	0.000	0.00000
Insulin	768.0	79.799479	115.244002	0.000	0.00000
BMI	768.0	31.992578	7.884160	0.000	27.30000
DiabetesPedigreeFunction	768.0	0.471876	0.331329	0.078	0.24375
Age	768.0	33.240885	11.760232	21.000	24.00000
Outcome	768.0	0.348958	0.476951	0.000	0.00000

	50%	75%	max
Pregnancies	3.0000	6.00000	17.00
Glucose	117.0000	140.25000	199.00
BloodPressure	72.0000	80.00000	122.00
SkinThickness	23.0000	32.00000	99.00
Insulin	30.5000	127.25000	846.00
BMI	32.0000	36.60000	67.10
DiabetesPedigreeFunction	0.3725	0.62625	2.42
Age	29.0000	41.00000	81.00
Outcome	0.0000	1.00000	1.00

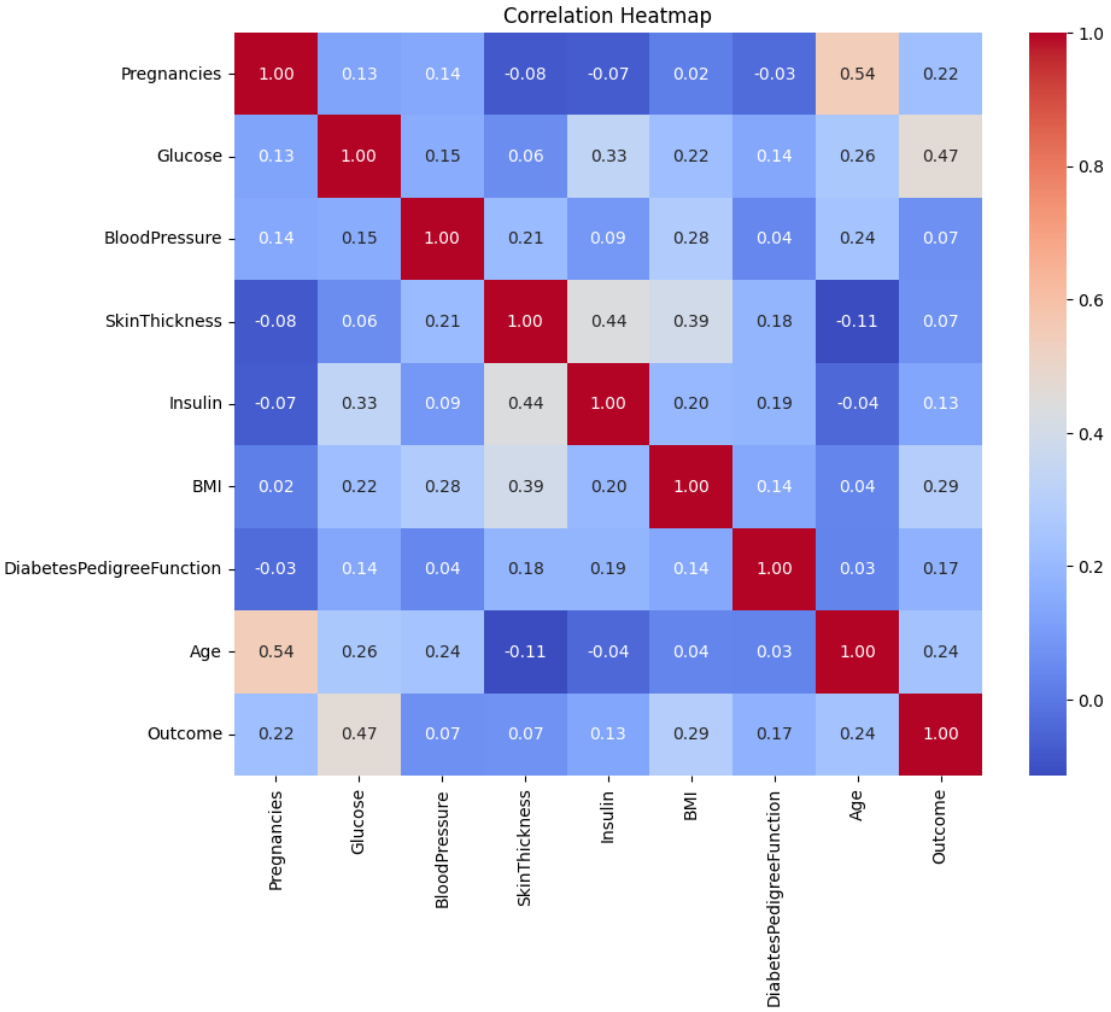
[20]:
```
features = df.drop('Outcome', axis=1).columns

plt.figure(figsize=(14, 12))

for i, col in enumerate(features, 1):
    plt.subplot(3, 3, i)
    sns.histplot(df[col], bins=20, kde=True)
    plt.title(col)
    plt.xlabel(col)
    plt.ylabel("Frequency")

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



[21]:
```
fig, axes = plt.subplots(3, 3, figsize=(15, 12))
axes = axes.flatten()

for i, col in enumerate(features):
    sns.boxplot(y=df[col], ax=axes[i])
    axes[i].set_title(f'Boxplot of {col}')


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



[22]:
```
plt.figure(figsize=(10,8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```



0.0.4 Email Classification

[23]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

df = pd.read_csv("dataset/email.csv")
df.head()
```

[23]:

	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...

[24]:
```
print("Info\n", df.info())
df.describe().T
```

```
<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
Info
 None
```

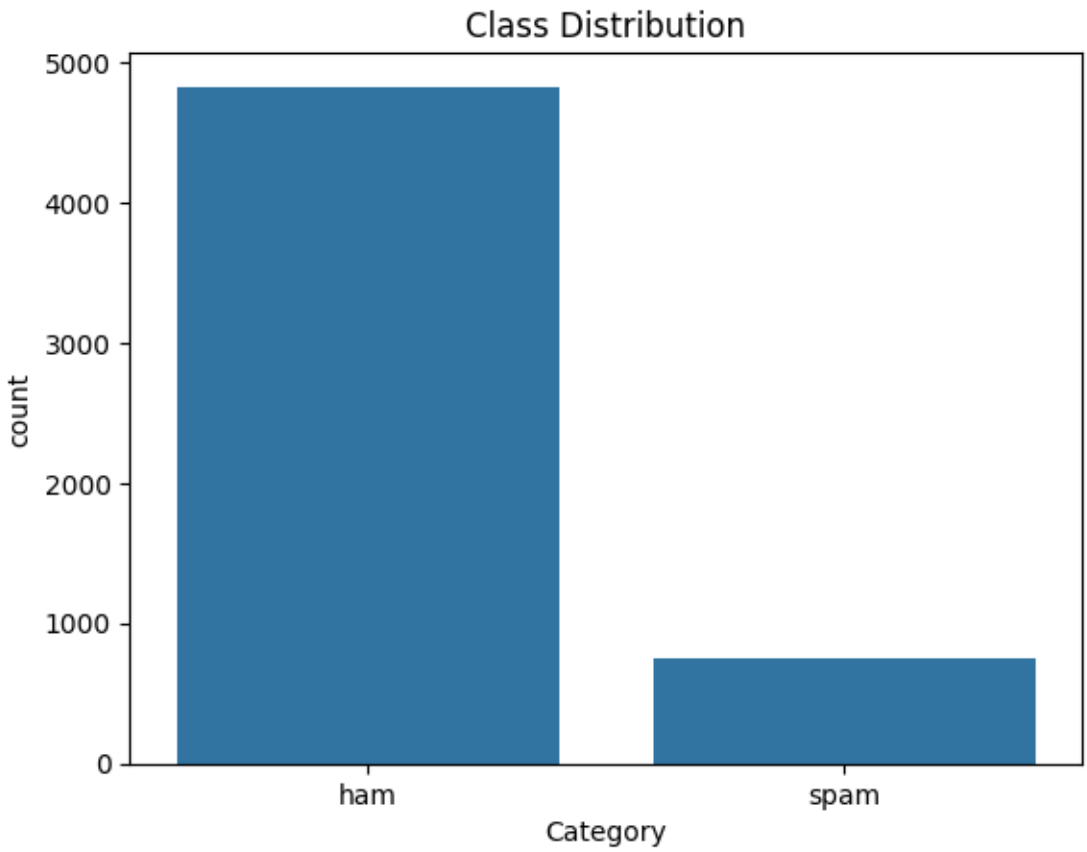
[24]:

	count	unique	top	freq
Category	5572	2	ham	4825
Message	5572	5157	Sorry, I'll call later	30

[25]:
```
print("Null Values\n", df.isnull().sum())
print("Counts of spam and Ham \n", df['Category'].value_counts())
```

```
Null Values
 Category    0
Message     0
dtype: int64
Counts of spam and Ham
 Category
ham     4825
spam     747
Name: count, dtype: int64
```

[26]:
```
sns.countplot(x='Category', data=df)
plt.title("Class Distribution")
plt.show()
```



[27]:
```
import re

def clean_text(text):
    text = text.lower()
    text = re.sub(r"http\S+", "", text)
    text = re.sub(r"[^a-z\s]", "", text)
    return text

df['clean_text'] = df['Message'].apply(clean_text)
```

[28]:
```
df['word_count'] = df['clean_text'].apply(lambda x: len(x.split()))
df['char_count'] = df['clean_text'].apply(len)
```

[29]:
```
df.head()
```

[29]:
```
  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...

                                          clean_text  word_count  char_count
0  go until jurong point crazy available only in ...          20         102
1                            ok lar joking wif u oni           6          23
2  free entry in  a wkly comp to win fa cup final...          25         124
3        u dun say so early hor u c already then say          11          43
4  nah i dont think he goes to usf he lives aroun...          13          59
```

[30]:
```
from collections import Counter

all_words = " ".join(df['clean_text']).split()
common_words = Counter(all_words).most_common(20)
common_words
```

[30]:
```
[('i', 2249),
 ('to', 2248),
 ('you', 2128),
 ('a', 1448),
 ('the', 1331),
 ('u', 1154),
 ('and', 971),
 ('is', 892),
 ('in', 889),
 ('me', 791),
 ('my', 759),
 ('for', 711),
 ('your', 677),
 ('it', 622),
 ('of', 622),
 ('call', 578),
 ('have', 573),
 ('on', 536),
 ('that', 514),
 ('are', 490)]
```

[31]:
```
spam_words = " ".join(df[df['Category']=="spam"]['clean_text']).split()
ham_words = " ".join(df[df['Category']=="ham"]['clean_text']).split()

print("Spam words most common \n\n", Counter(spam_words).most_common(15))
print("\nNot Spam common words \n", Counter(ham_words).most_common(15))
```

```
Spam words most common

 [('to', 686), ('a', 380), ('call', 347), ('you', 287), ('your', 263), ('free',
219), ('for', 204), ('the', 201), ('now', 190), ('or', 188), ('is', 157), ('u',
153), ('txt', 151), ('on', 145), ('ur', 144)]
```

```
Not Spam common words
 [('i', 2195), ('you', 1841), ('to', 1562), ('the', 1130), ('a', 1068), ('u',
1001), ('and', 849), ('in', 817), ('me', 761), ('my', 748), ('is', 735), ('it',
594), ('of', 525), ('for', 507), ('that', 488)]
```

Results and Discussions:

Dataset	**Type of ML Task**	**Suitable ML Algorithm**
Iris Dataset	Classification	K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree
Loan Amount Prediction	Regression	Linear Regression, Decision Tree Regressor, Random Forest Regressor
Diabetes Prediction	Classification	Logistic Regression, Support Vector Machine, Random Forest
Email Spam Detection	Text Classification	Naive Bayes, Support Vector Machine, Logistic Regression
Handwritten Character Recognition	Image Classification	Convolutional Neural Network (CNN), Support Vector Machine

Learning Practices

- Understood the fundamentals of data analysis using Python libraries such as NumPy, Pandas, Matplotlib, and Seaborn.
- Learnt to analyze datasets using descriptive statistics and exploratory data analysis techniques.
- Learnt to visualize data distributions and relationships using appropriate plots and charts.
- Learnt to identify suitable machine learning tasks such as classification and regression for different datasets.