DATE - 26\10\2023

TEAM ID - 3884

PROJECT TITLE - Age Based Customer Segmentation Using Data Science

Importing Libraries

In [5]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error
from sklearn.svm import SVR
from sklearn.linear_model import LinearRegression
```

In [6]:
```
dataset= pd.read_csv("C:\\Users\\sowen\\Downloads\\Mall_Customers.csv")
dataset
```

Out[6]:

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40
...	...	...	...	...	...
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

200 rows × 5 columns

Data Exploration

In [7]:
```
dataset
```

Out[7]:

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40
...	...	...	...	...	...
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

200 rows × 5 columns

In [8]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   CustomerID              200 non-null    int64 
 1   Genre                   200 non-null    object
 2   Age                     200 non-null    int64 
 3   Annual Income (k$)      200 non-null    int64 
 4   Spending Score (1-100)  200 non-null    int64 
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

In [9]:
```
dataset.drop('CustomerID', axis=1, inplace=True)
dataset.drop('Genre', axis=1, inplace=True)
dataset
```

Out[9]:

	Age	Annual Income (k$)	Spending Score (1-100)
0	19	15	39
1	21	15	81
2	20	16	6
3	23	16	77
4	31	17	40
...	...	...	...
195	35	120	79
196	45	126	28
197	32	126	74
198	32	137	18
199	30	137	83

200 rows × 3 columns

In [10]:
```
dataset.describe()
```

Out[10]:

	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000
mean	38.850000	60.560000	50.200000
std	13.969007	26.264721	25.823522
min	18.000000	15.000000	1.000000
25%	28.750000	41.500000	34.750000
50%	36.000000	61.500000	50.000000
75%	49.000000	78.000000	73.000000
max	70.000000	137.000000	99.000000

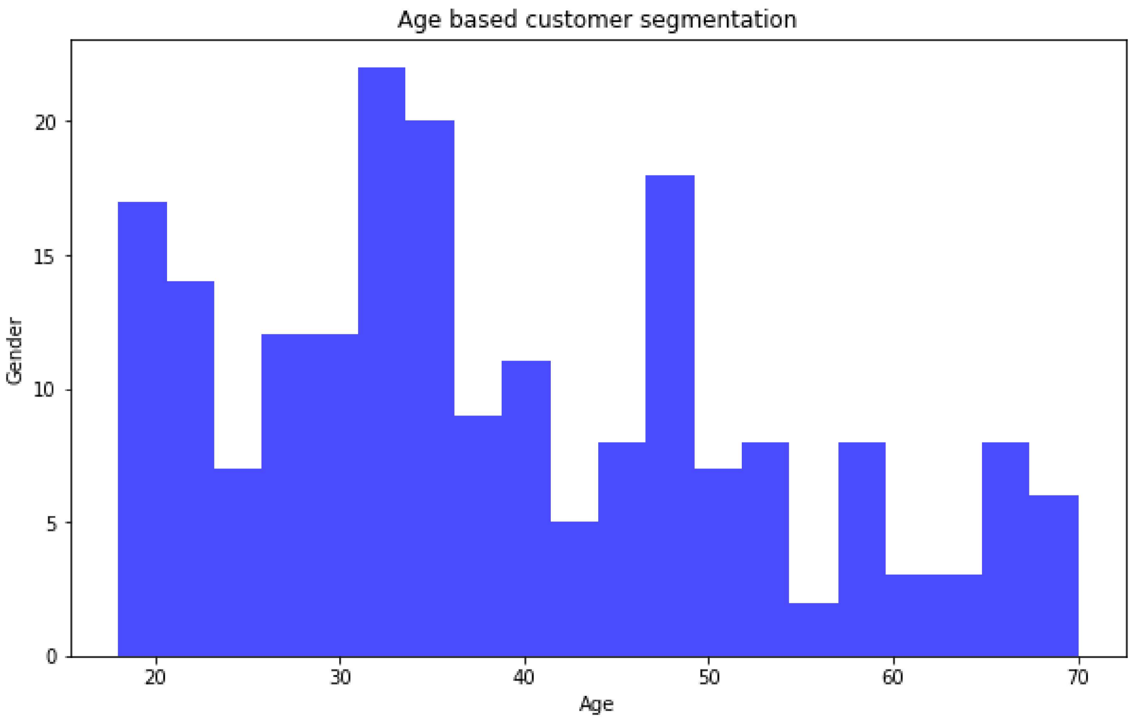
In [11]:
```
dataset.columns
```

Out[11]:
```
Index(['Age', 'Annual Income (k$)', 'Spending Score (1-100)'], dtype='obje
ct')
```

Data Visualization

1.Histogram

In [12]:
```
plt.figure(figsize=(10, 6))
plt.hist(dataset['Age'], bins=20, color='blue', alpha=0.7)
plt.title('Age based customer segmentation')
plt.xlabel('Age')
plt.ylabel('Gender')
plt.show()
```

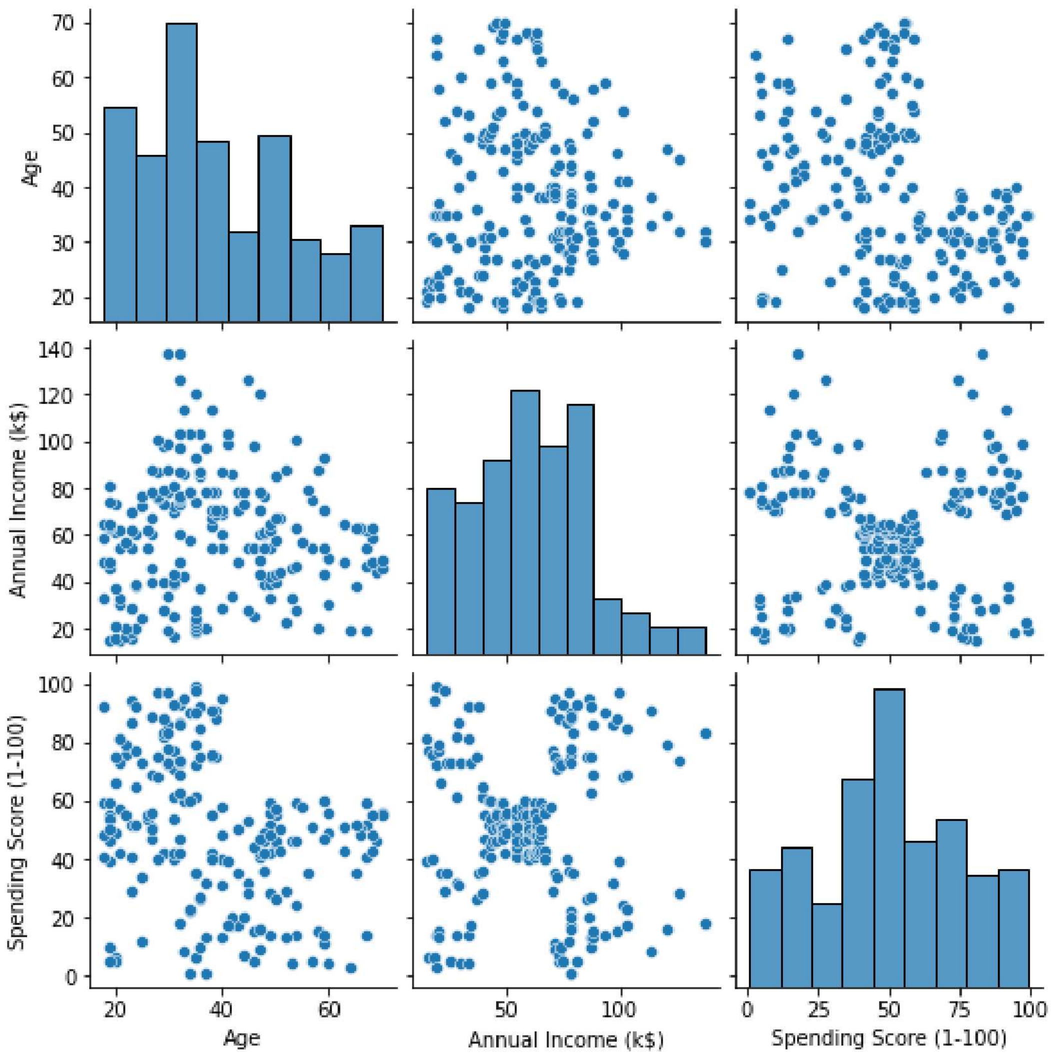


2. Bar chart

In [13]:
```
plt.figure(figsize=(12,6))
sns.pairplot(dataset)
```

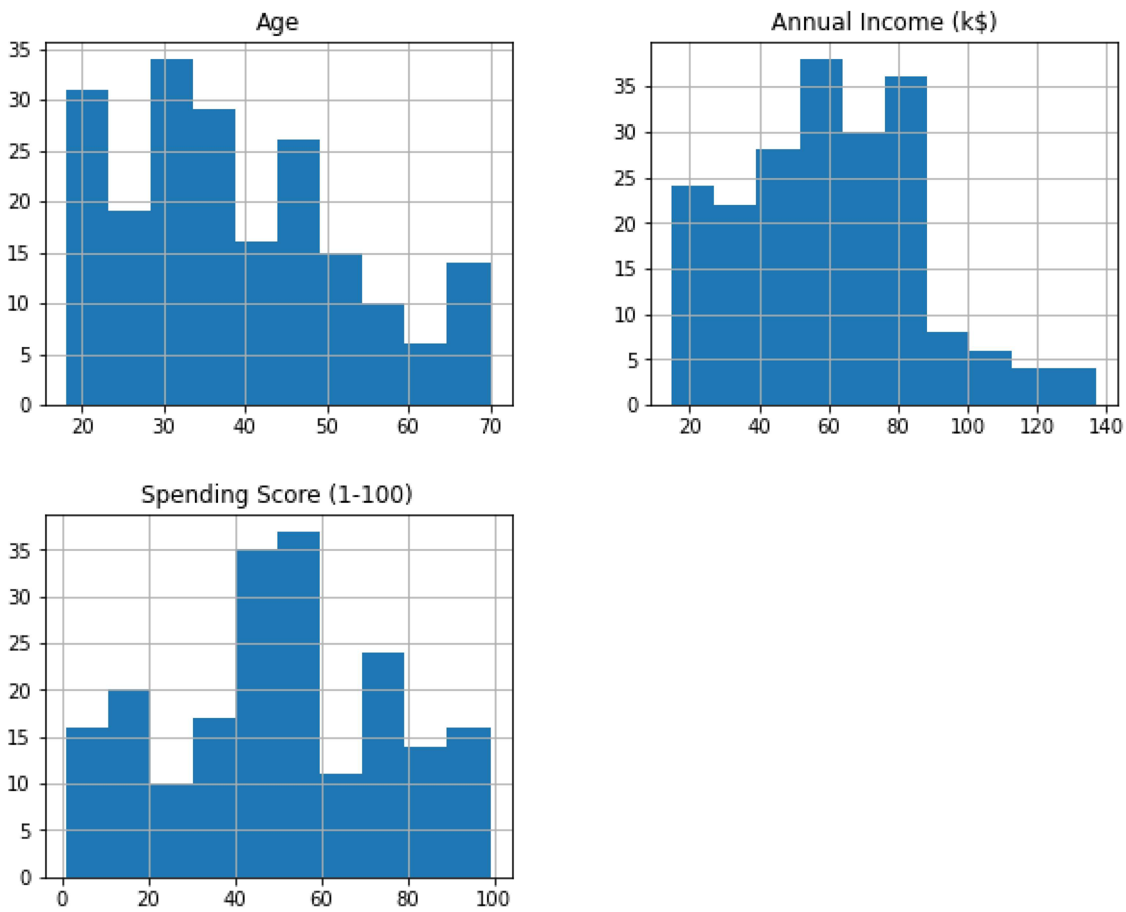
Out[13]:
```
<seaborn.axisgrid.PairGrid at 0x1e03726b6d0>
```

```
<Figure size 864x432 with 0 Axes>
```



In [14]:
```python
dataset.hist(figsize=(10,8))
```

Out[14]:
```
array([[<AxesSubplot:title={'center':'Age'}>,
        <AxesSubplot:title={'center':'Annual Income (k$)'}>],
       [<AxesSubplot:title={'center':'Spending Score (1-100)'}>,
        <AxesSubplot:>]], dtype=object)
```



Visualising Correlation

In [15]:
```python
dataset.corr()
```

Out[15]:

	Age	Annual Income (k$)	Spending Score (1-100)
Age	1.000000	-0.012398	-0.327227
Annual Income (k$)	-0.012398	1.000000	0.009903
Spending Score (1-100)	-0.327227	0.009903	1.000000

In [16]:
```
plt.figure(figsize=(10,5))
sns.heatmap(dataset.corr(), annot=True)
```

Out[16]: <AxesSubplot:>

By using PCA Algorithm

In [17]:
```
X = dataset.drop('Spending Score (1-100)', axis=1)
y = dataset['Spending Score (1-100)']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
n_components = 2
```

In [18]:
```
pca = PCA(n_components=n_components)
X_pca = pca.fit_transform(X_scaled)
X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size=0.2
model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
```

Mean Squared Error: 483.55682175408344

Training model:1_ Decision Tree Regressor

In [19]:
```
decision_tree = DecisionTreeRegressor()
decision_tree.fit(X_train, y_train)
y_pred = decision_tree.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
print("Mean Squared Error:", mse)
```

Mean Squared Error: 1073.35

Training model:2_Support vector machine algorithm

In [20]:
```
svm = SVR(kernel='rbf', C=1.0, gamma='scale')
svm.fit(X_train, y_train)
```

Out[20]:
```
SVR()
```

In [21]:
```
y_pred = svm.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
```

```
Mean Squared Error: 524.8207652112172
```

Training model:3_Linear Regression

In [23]:
```
regression_model = LinearRegression()
regression_model.fit(X_train, y_train)

y_pred = regression_model.predict(X_test)

mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Squared Error (MSE): {mse}")
print(f"R-squared (R2): {r2}")
```

```
Mean Squared Error (MSE): 483.55682175408344
R-squared (R2): 0.01963177813218009
```