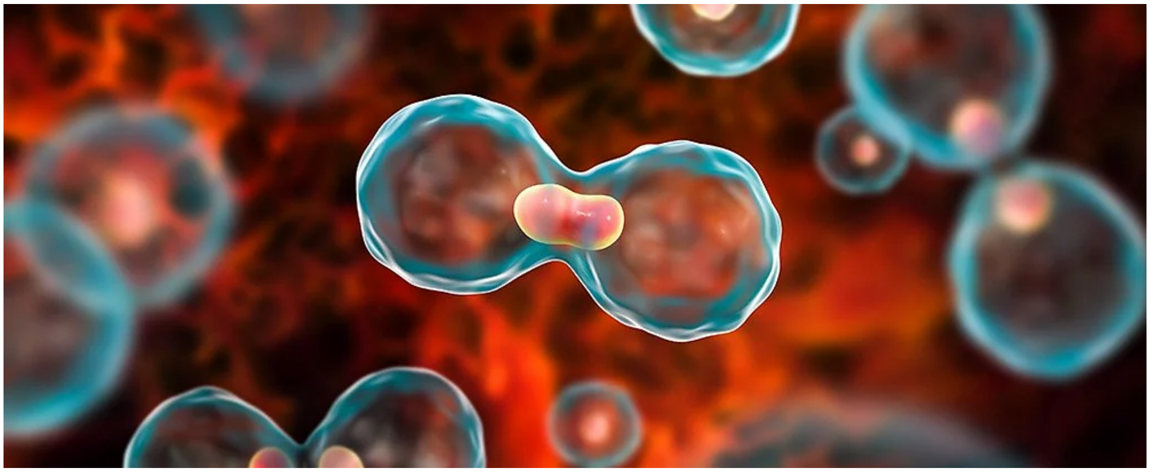


Introduction

The Haberman Survival dataset, named after researcher R.A. Haberman, encompasses medical records of breast cancer surgery patients at the University of Chicago's Billings Hospital from 1958 to 1970. Comprising 306 instances, it includes patient age, year of operation, and the number of positive axillary nodes. The dataset is a prominent resource for survival analysis, particularly in predicting whether patients survive for a minimum of 5 years post-surgery. Widely utilized in machine learning, it serves as a fundamental benchmark for developing and evaluating algorithms, making significant contributions to the field of medical research and statistical analysis.

In [1]:

```
# Haverman dataset
```

1 import Necessary Library

In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
```

2 import Dataset

In [3]:

```
df = pd.read_csv("/kaggle/input/haberman/haberman.csv")
```

3 Data Analysis

In [4]:

```
df.head()
```

Out[4]:

	Age	Year	Nodes	Status
0	30	62	3	1

1	30	65	0	1
2	31	59	2	1
3	31	65	4	1
4	33	58	10	1

In [5]:
```python
df.tail()
```

Out[5]:

	Age	Year	Nodes	Status
300	75	62	1	1
301	76	67	0	1
302	77	65	3	1
303	78	65	1	2
304	83	58	2	2

In [6]:
```python
df.shape
```

Out[6]:
```
(305, 4)
```

In [7]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 305 entries, 0 to 304
Data columns (total 4 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Age     305 non-null    int64
 1   Year    305 non-null    int64
 2   Nodes   305 non-null    int64
 3   Status  305 non-null    int64
dtypes: int64(4)
memory usage: 9.7 KB
```

In [8]:
```python
df.dtypes
```

Out[8]:
```
Age       int64
Year      int64
Nodes     int64
Status    int64
dtype: object
```

In [9]:
```python
df.describe()
```

Out[9]:

	Age	Year	Nodes	Status
count	305.000000	305.000000	305.000000	305.000000
mean	52.531148	62.849180	4.036066	1.265574
std	10.744024	3.254078	7.199370	0.442364
min	30.000000	58.000000	0.000000	1.000000

25%	44.000000	60.000000	0.000000	1.000000
50%	52.000000	63.000000	1.000000	1.000000
75%	61.000000	66.000000	4.000000	2.000000
max	83.000000	69.000000	52.000000	2.000000

In [10]:
```
df.corr()
```

Out[10]:

	Age	Year	Nodes	Status
Age	1.000000	0.092623	-0.066548	0.064351
Year	0.092623	1.000000	-0.003277	-0.004076
Nodes	-0.066548	-0.003277	1.000000	0.286191
Status	0.064351	-0.004076	0.286191	1.000000

In [11]:
```
df.ndim
```

Out[11]: 2

In [12]:
```
df.columns
```

Out[12]:
```
Index(['Age', 'Year', 'Nodes', 'Status'], dtype='object')
```

In [13]:
```
df["Status"].value_counts()
```

Out[13]:
```
Status
1    224
2     81
Name: count, dtype: int64
```

4 Data cleaning and Preprocessing:

In [14]:
```
df.isnull().sum()
```

Out[14]:
```
Age       0
Year      0
Nodes     0
Status    0
dtype: int64
```

In [15]:
```
df['Status'].value_counts()
```

Out[15]:
```
Status
1    224
2     81
Name: count, dtype: int64
```

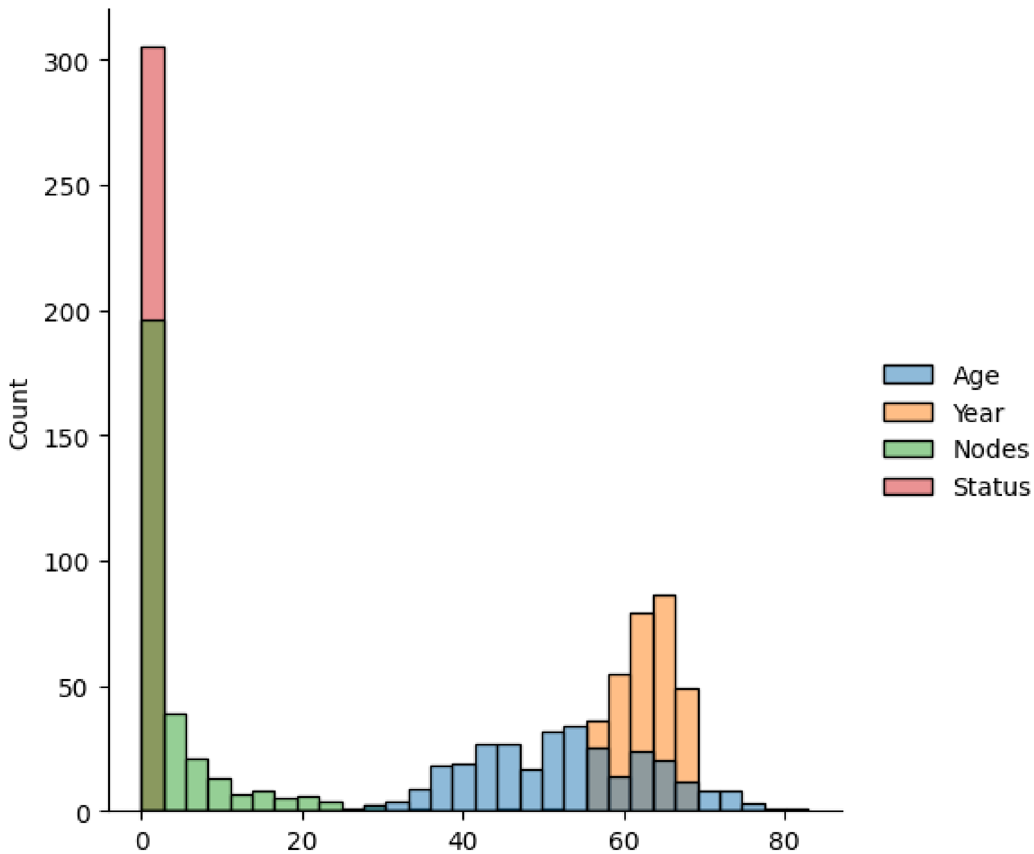
5| Data visualisation 📊 📉

EDA (Exploratory Data Analysis)

5.1 displot

In [16]:

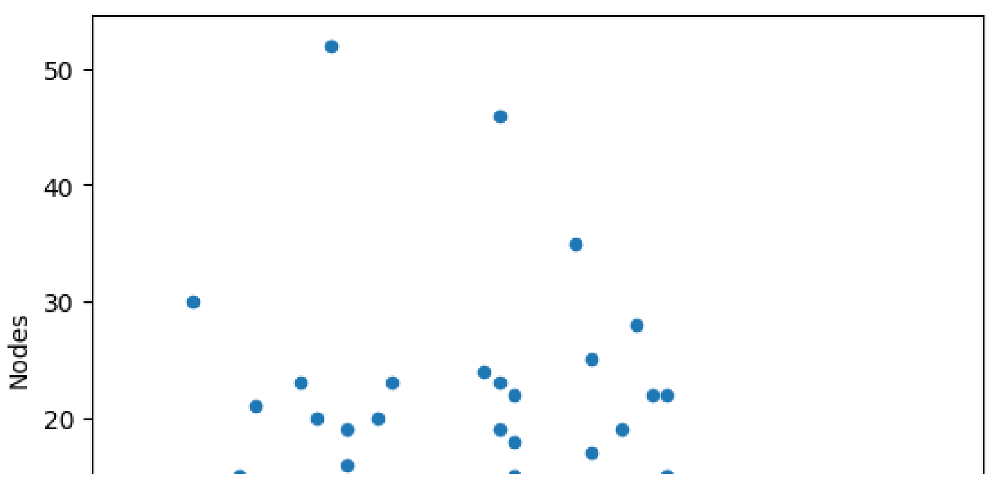
```
sns.displot(df, kde=False, bins=30)
plt.show()
```

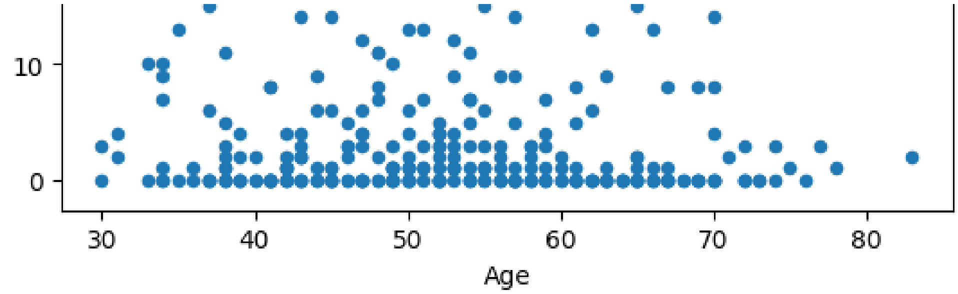


5.2 Scatter Plot

In [17]:

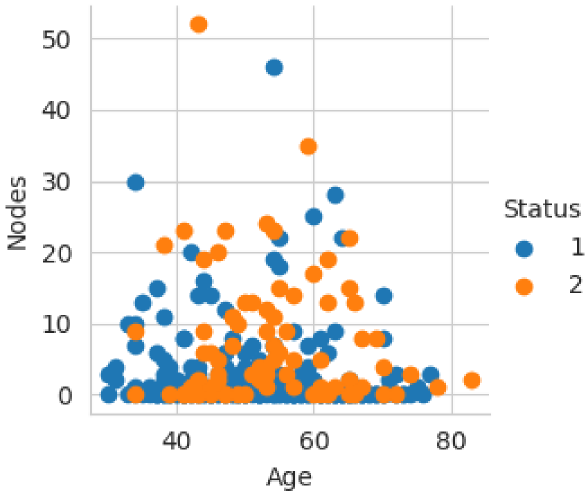
```
df.plot(kind='scatter', x='Age', y='Nodes')
plt.show()
```





In [18]:

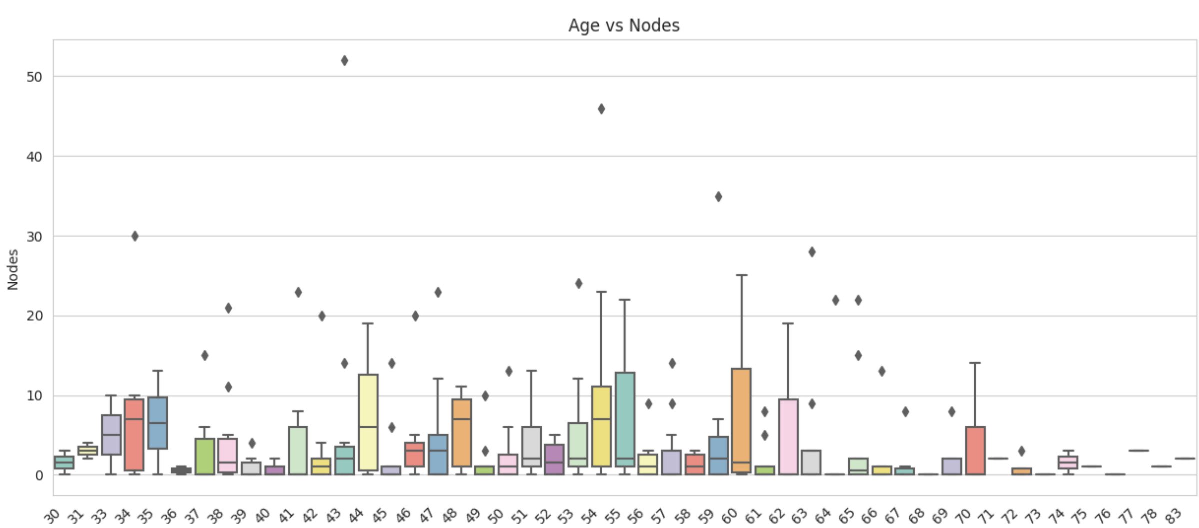
```
sns.set_style("whitegrid");
sns.FacetGrid(df, hue="Status").map(plt.scatter, "Age", "Nodes").add_legend();
plt.show();
```



5.3 boxplot

In [19]:

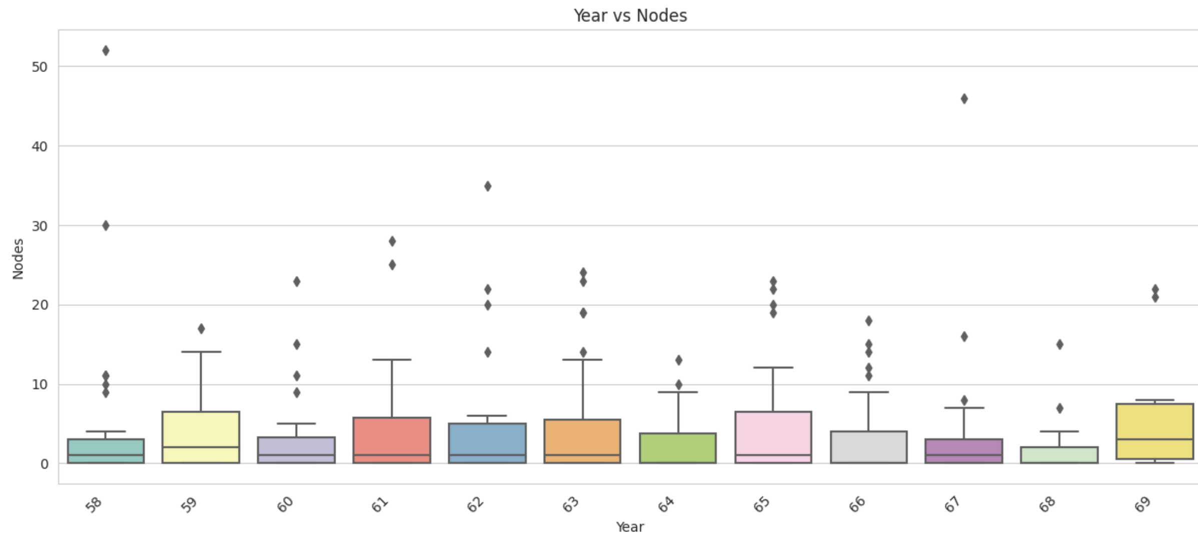
```
# sepal_length vs sepal_width boxplot

plt.figure(figsize=(15, 6))
sns.boxplot(x='Age', y='Nodes', data=df, palette='Set3')
plt.title('Age vs Nodes')
plt.xlabel('Age')
plt.ylabel('Nodes')
plt.xticks(rotation=45, ha='right')
plt.show()
```



Age

In [20]:

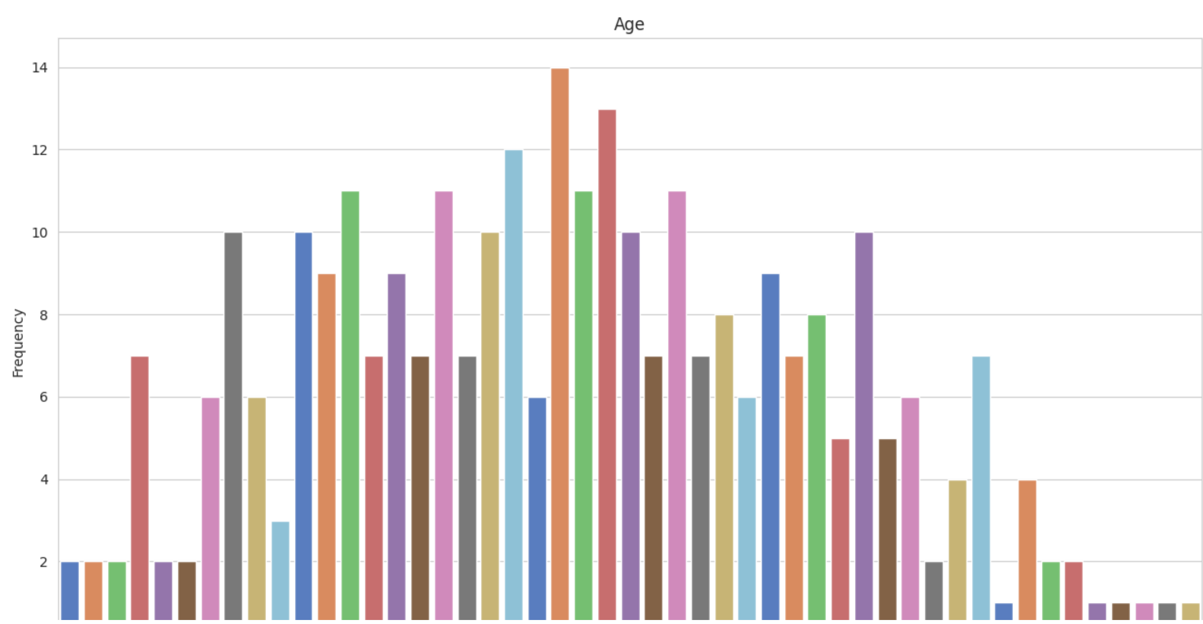
```
# sepal_length vs sepal_width boxplot

plt.figure(figsize=(15, 6))
sns.boxplot(x='Year', y='Nodes', data=df, palette='Set3')
plt.title('Year vs Nodes')
plt.xlabel('Year')
plt.ylabel('Nodes')
plt.xticks(rotation=45, ha='right')
plt.show()
```



5.4 countplot

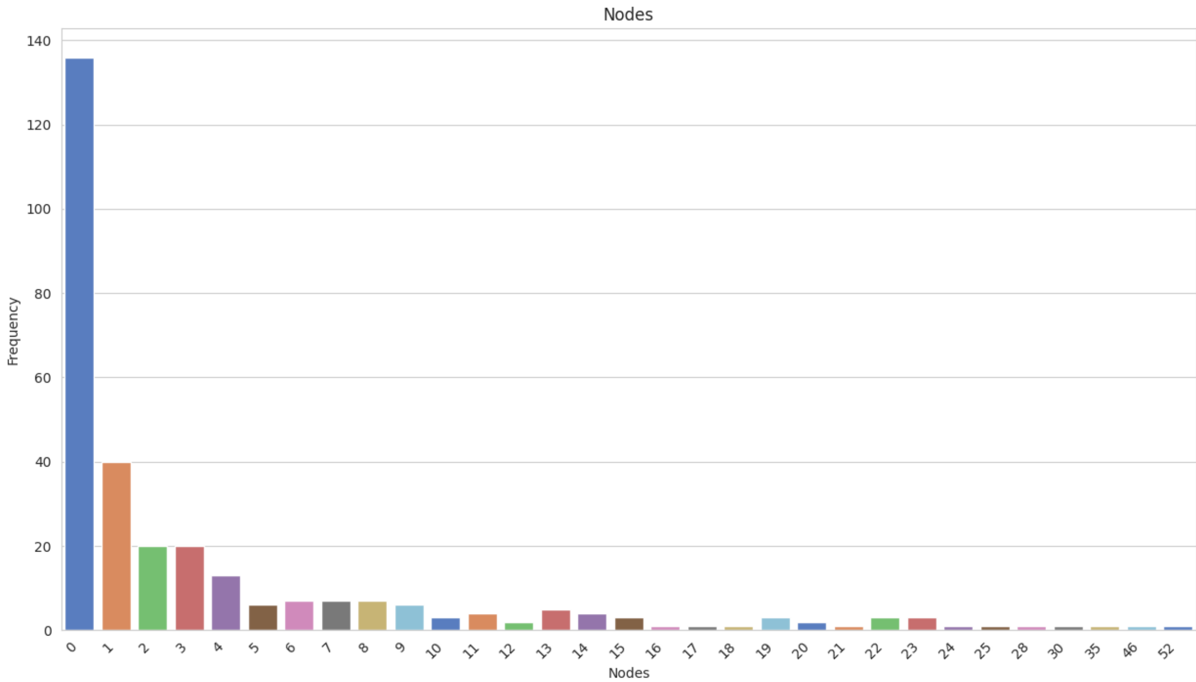
In [21]:

```
# sepal_length
plt.figure(figsize=(15, 8))
sns.countplot(x='Age', data=df, palette='muted')
plt.title('Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.xticks(rotation=45, ha='right')
plt.show()
```



In [22]:

```
# sepal_length
plt.figure(figsize=(15, 8))
sns.countplot(x='Nodes', data=df, palette='muted')
plt.title('Nodes')
plt.xlabel('Nodes')
plt.ylabel('Frequency')
plt.xticks(rotation=45, ha='right')
plt.show()
```

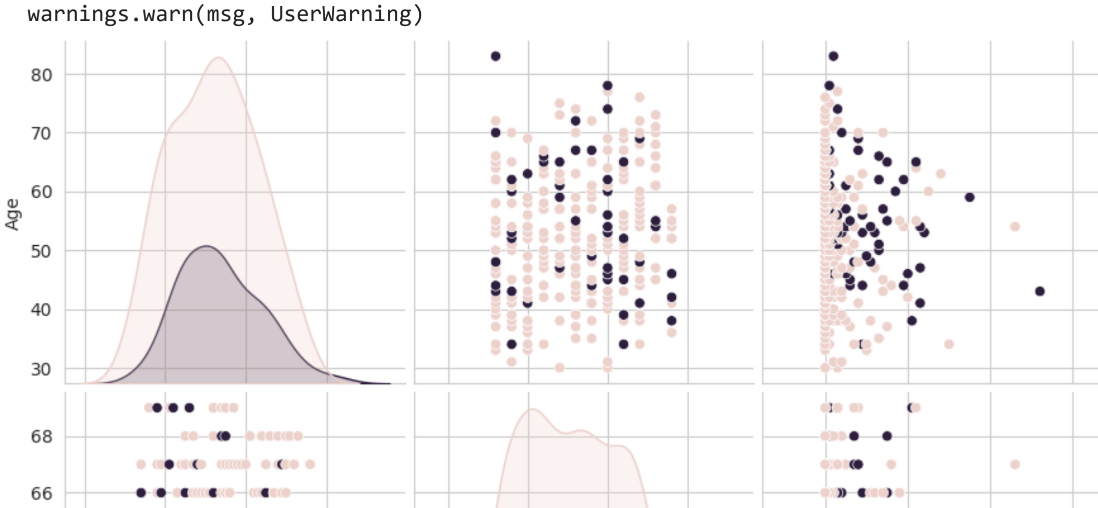


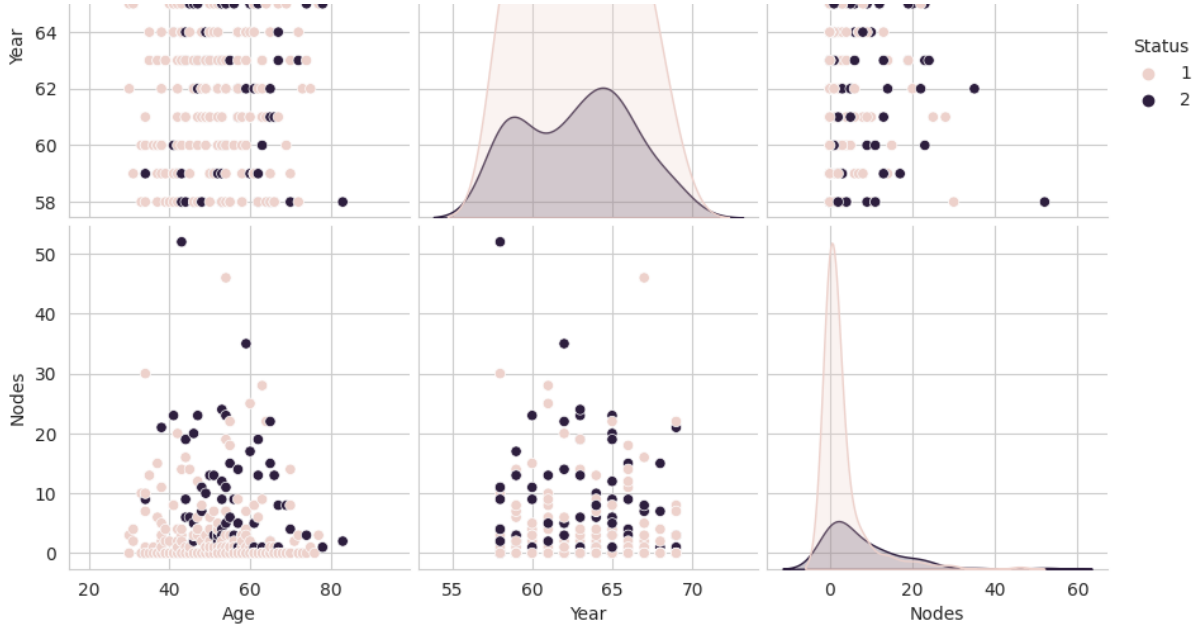
5.5 pairplot

In [23]:

```
sns.set_style("whitegrid")
sns.pairplot(df, hue="Status", size=3)
plt.show()
```

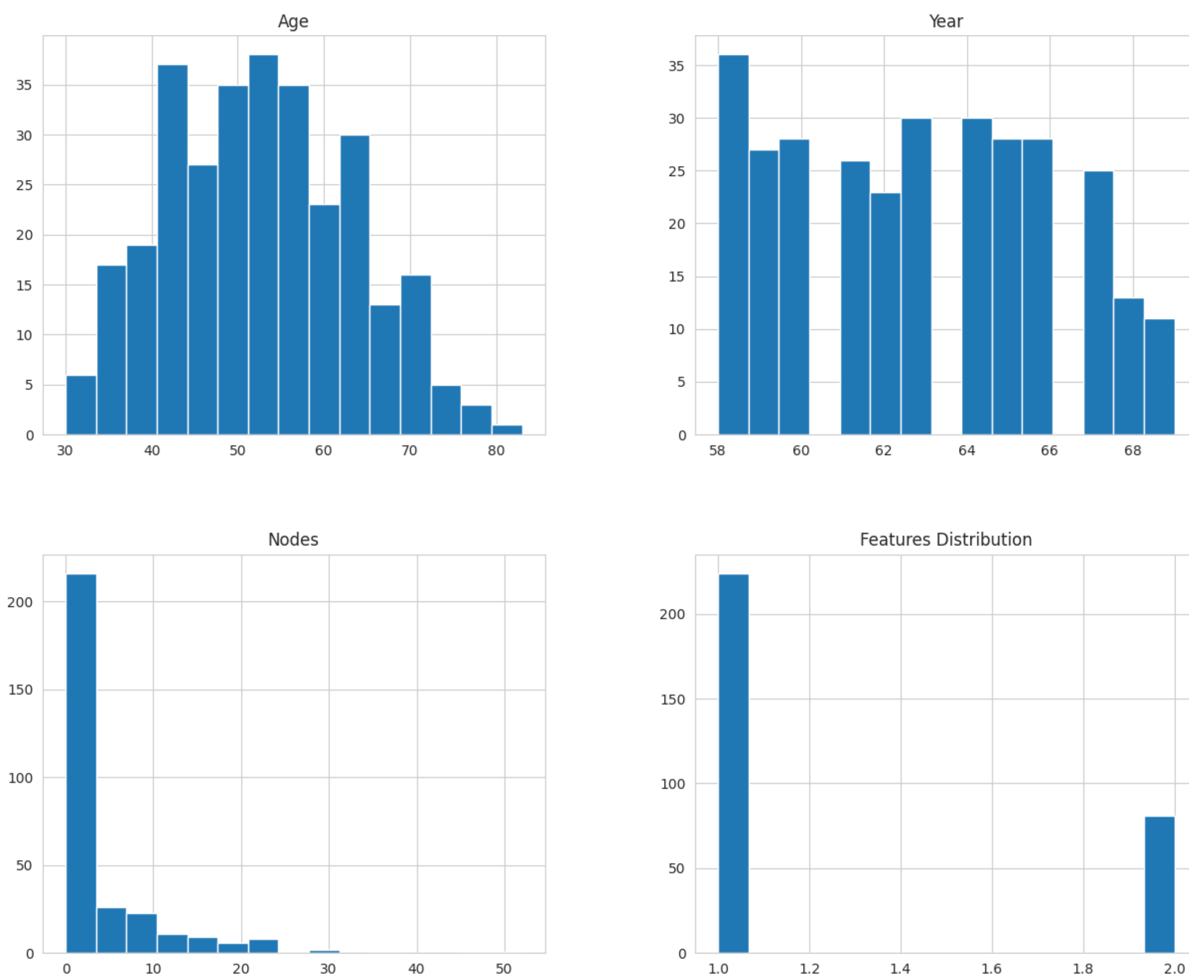
```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:2095: UserWarning: The `size` par
ameter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```





5.6 Hist Plot

In [24]:
```
df.hist(figsize=(15,12),bins = 15)
plt.title("Features Distribution")
plt.show()
```

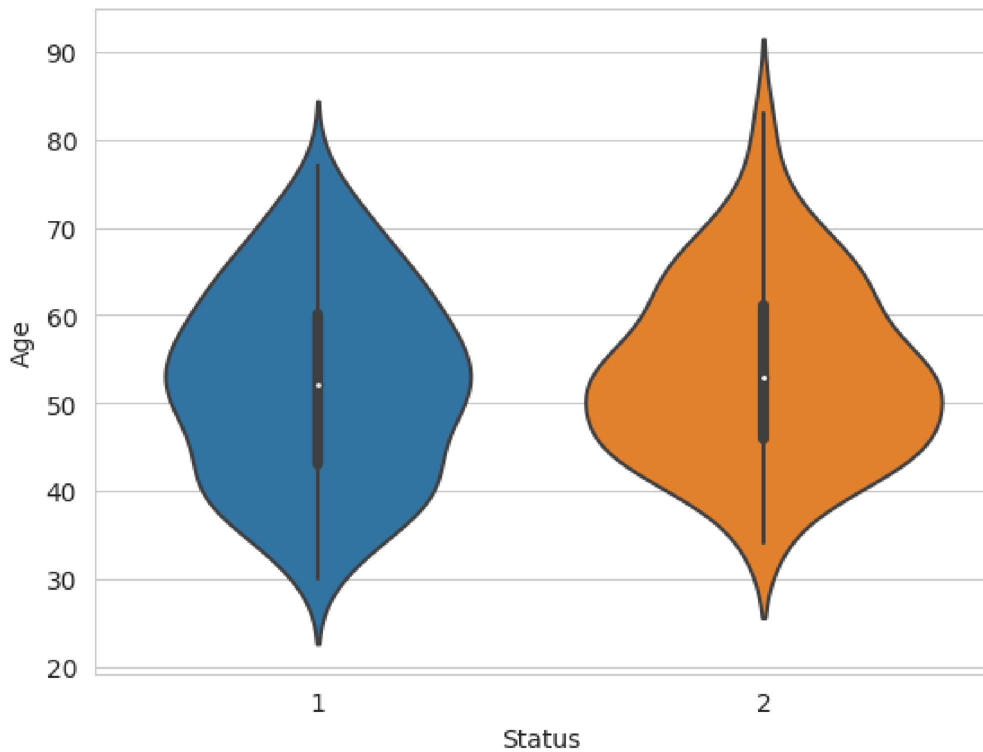


5.7 violinplot

5.7 violinplot

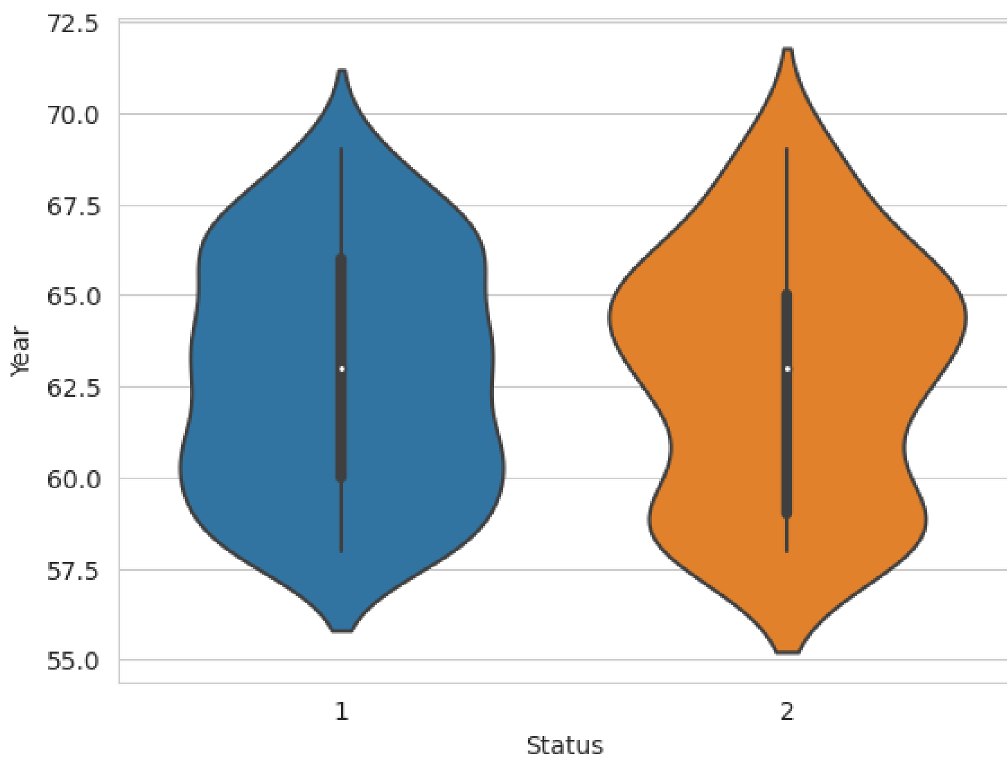
In [25]:
```
sns.violinplot(x="Status",y="Age", data=df, size = 8)
```

Out[25]: <Axes: xlabel='Status', ylabel='Age'>



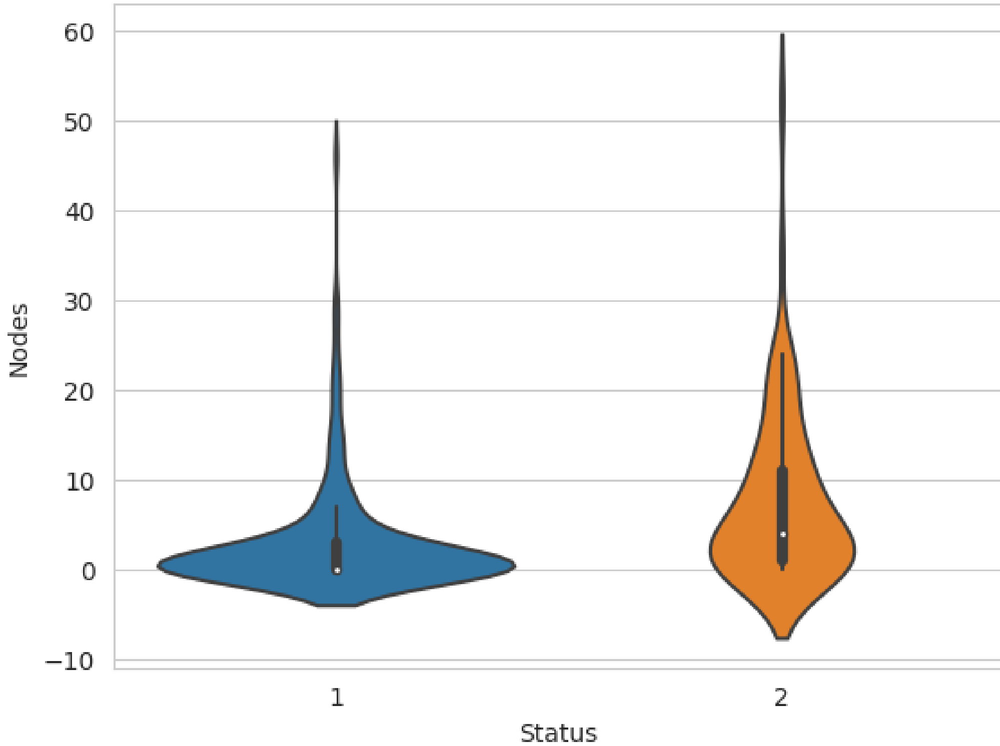
In [26]:
```
sns.violinplot(x="Status",y="Year", data=df, size = 8)
```

Out[26]: <Axes: xlabel='Status', ylabel='Year'>



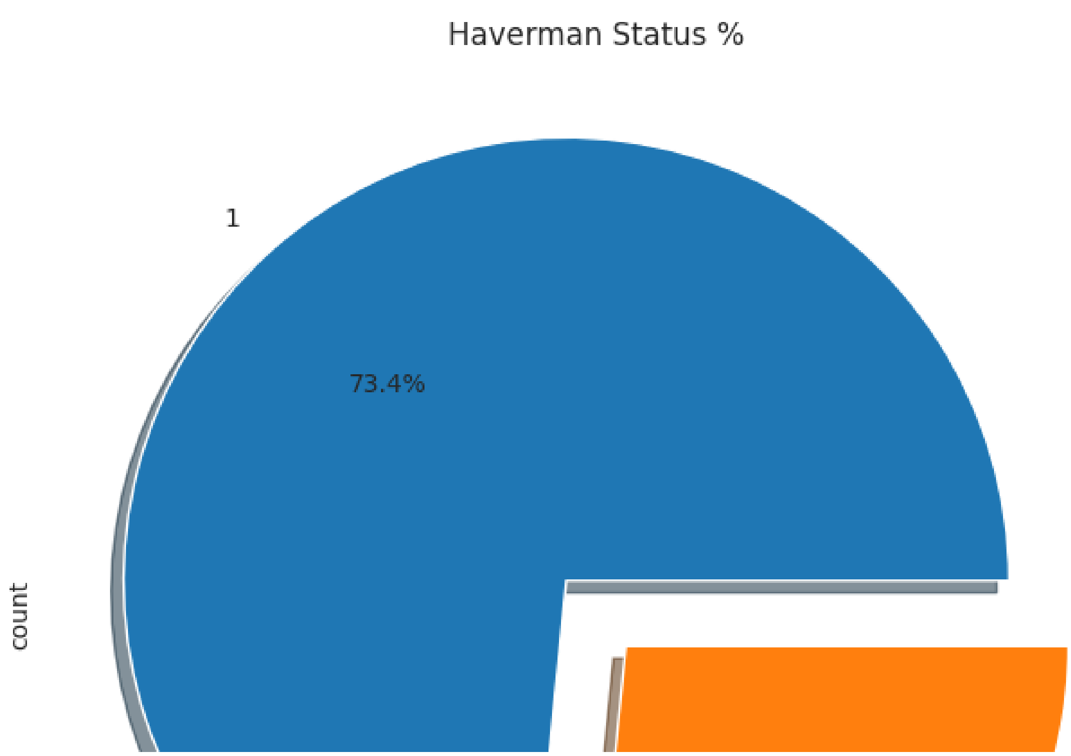
In [27]:
```
sns.violinplot(x="Status",y="Nodes", data=df, size = 8)
```

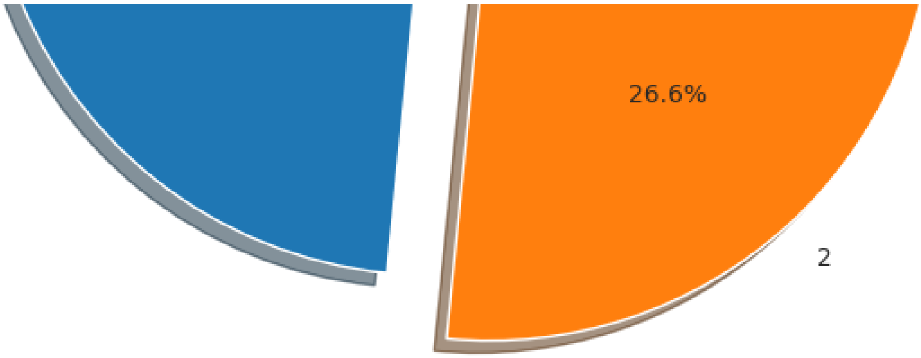
Out[27]: <Axes: xlabel='Status', ylabel='Nodes'>



5.8 Pie Plot

In [28]:
```
ax=plt.subplots(1,1,figsize=(10,8))
df['Status'].value_counts().plot.pie(explode=[0.1,0.1],autopct='%1.1f%%',shadow=True,figsiz
plt.title("Haverman Status %")
plt.show()
```





6 | Split the Dataset

In [29]:
```
from sklearn.model_selection import train_test_split
```

In [30]:
```
X = df[["Age", "Year", "Nodes"]]
```

In [31]:
```
y = df['Status']
```

In [32]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.2, random_state=42)
```

In [33]:
```
X_train.shape,X_test.shape,y_train.shape,y_test.shape
```

Out[33]:
```
((244, 3), (61, 3), (244,), (61,))
```

7 | PCA (Principal Component Analysis)

In [34]:
```
from sklearn.decomposition import PCA
```

In [35]:
```
pca = PCA(n_components=2)
```

In [36]:
```
pca
```

Out[36]:
```
PCA(n_components=2)
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [37]:
```
X_pca = pca.fit_transform(X)
```

In [38]:
```
X_pca[0]
```

```
X_pca[0]
```

Out[38]: array([-22.39138751, -2.83734654])

In [39]:

```
print("Explained Variance Ratio:")
print(pca.explained_variance_ratio_)
```

```
Explained Variance Ratio:
[0.65192362 0.28910141]
```

In [40]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_ft = scaler.fit_transform(X)
```

In [41]:

```
X_ft[0]
```

Out[41]: array([0.   , 0.36363636, 0.05769231])

In [42]:

```
X_ft[1]
```

Out[42]: array([0.   , 0.63636364, 0.   ])

⚙ Machine Learning Algorithm

Algorithm 🔄

(1) KNN 🔄

In [43]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
```

In [44]:

```
knn_classifier = KNeighborsClassifier(n_neighbors=3)
```

In [45]:

```
knn_classifier.fit(X_train, y_train)
```

Out[45]: KNeighborsClassifier(n_neighbors=3)

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [46]:

```
train_predictions = knn_classifier.predict(X_train)

train_accuracy1 = accuracy_score(y_train, train_predictions)
```

In [47]:

```
test_predictions = knn_classifier.predict(X_test)

test_accuracy1 = accuracy_score(y_test, test_predictions)
```

```
test_accuracy1 = accuracy_score(y_test, test_predictions)
```

In [48]:

```
print(f"Training Accuracy: {train_accuracy1}")
print(f"Testing Accuracy: {test_accuracy1}")
```

```
Training Accuracy: 0.8647540983606558
Testing Accuracy: 0.6885245901639344
```

(2) Naive Bayes classifier

In [49]:

```
from sklearn.naive_bayes import GaussianNB
from sklearn.naive_bayes import BernoulliNB
from sklearn.naive_bayes import MultinomialNB

from sklearn import metrics
```

In [50]:

```
# GaussianNB
```

In [51]:

```
G_classifier = GaussianNB()
```

In [52]:

```
G_classifier.fit(X_train, y_train)
```

Out[52]:

```
GaussianNB()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [53]:

```
train_predictions = G_classifier.predict(X_train)

train_accuracy21 = accuracy_score(y_train, train_predictions)
```

In [54]:

```
test_predictions = G_classifier.predict(X_test)

test_accuracy21 = accuracy_score(y_test, test_predictions)
```

In [55]:

```
print(f"Training Accuracy: {train_accuracy21}")
print(f"Testing Accuracy: {test_accuracy21}")
```

```
Training Accuracy: 0.75
Testing Accuracy: 0.7704918032786885
```

In [56]:

```
B_classifier = BernoulliNB()
```

In [57]:

```
B_classifier.fit(X_train, y_train)
```

Out[57]:

```
BernoulliNB()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [58]:
```
train_predictions = B_classifier.predict(X_train)

train_accuracy22 = accuracy_score(y_train, train_predictions)
```

In [59]:
```
test_predictions = G_classifier.predict(X_test)

test_accuracy22 = accuracy_score(y_test, test_predictions)
```

In [60]:
```
print(f"Training Accuracy: {train_accuracy22}")
print(f"Testing Accuracy: {test_accuracy22}")
```

```
Training Accuracy: 0.7254098360655737
Testing Accuracy: 0.7704918032786885
```

In [61]:
```
# MultinomialNB
```

In [62]:
```
M_classifier = MultinomialNB()
```

In [63]:
```
M_classifier.fit(X_train, y_train)
```

Out[63]:
```
MultinomialNB()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [64]:
```
train_predictions = M_classifier.predict(X_train)

train_accuracy23 = accuracy_score(y_train, train_predictions)
```

In [65]:
```
test_predictions = M_classifier.predict(X_test)

test_accuracy23 = accuracy_score(y_test, test_predictions)
```

In [66]:
```
print(f"Training Accuracy: {train_accuracy23}")
print(f"Testing Accuracy: {test_accuracy23}")
```

```
Training Accuracy: 0.7336065573770492
Testing Accuracy: 0.7377049180327869
```

👉 GaussianNB

Training Accuracy: 0.75

Testing Accuracy: 0.7704918032786885

👉 BernoulliNB

Training Accuracy: 0.7254098360655737

Testing Accuracy: 0.7704918032786885

👉 MultinomialNB

Training Accuracy: 0.7336065573770492

Testing Accuracy: 0.7377049180327869

Being the best of them | 🔥 GaussianNB |

(3) Decision Tree 🔄

In [67]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [68]:
```
clf = DecisionTreeClassifier()
```

In [69]:
```
clf.fit(X_train, y_train)
```

Out[69]:
```
DecisionTreeClassifier()
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [70]:
```
train_predictions = clf.predict(X_train)

train_accuracy3 = accuracy_score(y_train, train_predictions)
```

In [71]:
```
test_predictions = clf.predict(X_test)

test_accuracy3 = accuracy_score(y_test, test_predictions)
```

In [72]:
```
print(f"Training Accuracy: {train_accuracy3}")
print(f"Testing Accuracy: {test_accuracy3}")
```

```
Training Accuracy: 0.9754098360655737
Testing Accuracy: 0.7540983606557377
```

(4) Random Forest

In [73]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [74]:
```
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
```

In [75]:
```
rf_classifier.fit(X_train, y_train)
```

Out[75]:
```
RandomForestClassifier(random_state=42)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [76]:
```
train_predictions = rf_classifier.predict(X_train)

train_accuracy4 = accuracy_score(y_train, train_predictions)
```

In [77]:
```
test_predictions = rf_classifier.predict(X_test)

test_accuracy4 = accuracy_score(y_test, test_predictions)
```

In [78]:
```
print(f"Training Accuracy: {train_accuracy4}")
print(f"Testing Accuracy: {test_accuracy4}")
```

```
Training Accuracy: 0.9754098360655737
Testing Accuracy: 0.7868852459016393
```

(5) Boosting Algorithm

In [79]:
```
from sklearn.ensemble import AdaBoostClassifier
```

In [80]:
```
base_classifier = DecisionTreeClassifier(max_depth=1)
```

In [81]:
```
adaboost_classifie = AdaBoostClassifier(base_classifier, n_estimators=50, random_state=42
```

In [82]:
```
adaboost_classifie.fit(X_train, y_train)
```

Out[82]:
```
AdaBoostClassifier(estimator=DecisionTreeClassifier(max_depth=1),
                   random_state=42)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [83]:
```
train_predictions = adaboost_classifier.predict(X_train)

train_accuracy5 = accuracy_score(y_train, train_predictions)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[83], line 1
----> 1 train_predictions = adaboost_classifier.predict(X_train)
      3 train_accuracy5 = accuracy_score(y_train, train_predictions)

NameError: name 'adaboost_classifier' is not defined
```

In [ ]:
```
test_predictions = adaboost_classifier.predict(X_test)
```

```
test_accuracy5 = accuracy_score(y_test, test_predictions)
```

In [ ]:

```
print(f"Training Accuracy: {train_accuracy5}")
print(f"Testing Accuracy: {test_accuracy5}")
```

(6).SVM

In [84]:

```
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
```

In [85]:

```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [86]:

```
svm_classifier = SVC(kernel='linear', C=1.0)
```

In [87]:

```
svm_classifier.fit(X_train, y_train)
```

Out[87]:

```
SVC(kernel='linear')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [88]:

```
train_predictions = svm_classifier.predict(X_train)

train_accuracy6 = accuracy_score(y_train, train_predictions)
```

In [89]:

```
test_predictions = svm_classifier.predict(X_test)

test_accuracy6 = accuracy_score(y_test, test_predictions)
```

In [90]:

```
print(f"Training Accuracy: {train_accuracy6}")
print(f"Testing Accuracy: {test_accuracy6}")
```

```
Training Accuracy: 0.7213114754098361
Testing Accuracy: 0.7704918032786885
```

(7). Logistic Regression

In [91]:

```
from sklearn import linear_model
```

In [92]:

```
lrg = linear_model.LogisticRegression()
```

In [93]:

```
lrg.fit(X_train, y_train)
```

Out[93]: LogisticRegression()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [94]:
```
train_predictions = lrg.predict(X_train)

train_accuracy7 = accuracy_score(y_train, train_predictions)
```

In [95]:
```
test_predictions = lrg.predict(X_test)

test_accuracy7 = accuracy_score(y_test, test_predictions)
```

In [96]:
```
print(f"Training Accuracy: {train_accuracy7}")
print(f"Testing Accuracy: {test_accuracy7}")
```

```
Training Accuracy: 0.7377049180327869
Testing Accuracy: 0.7704918032786885
```

(8).Linear Regression

In [97]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
```

In [98]:
```
model = LinearRegression()
```

In [99]:
```
model.fit(X_train, y_train)
```

Out[99]: LinearRegression()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [100…
```
train_predictions = clf.predict(X_train)

train_accuracy8 = accuracy_score(y_train, train_predictions)
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/base.py:439: UserWarning: X does not have va
lid feature names, but DecisionTreeClassifier was fitted with feature names
  warnings.warn(
```

In [101…
```
test_predictions = clf.predict(X_test)

test_accuracy8 = accuracy_score(y_test, test_predictions)
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/base.py:439: UserWarning: X does not have va
lid feature names, but DecisionTreeClassifier was fitted with feature names
  warnings.warn(
```

In [102…
```
print(f"Training Accuracy: {train_accuracy8}")
```

```
print(f"Testing Accuracy: {test_accuracy8}")
```

```
Training Accuracy: 0.7254098360655737
Testing Accuracy: 0.7704918032786885
```

(9).Gradient Boosting Machines (GBM)

In [103…

```
from sklearn.ensemble import GradientBoostingClassifier
```

In [104…

```
model = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, max_depth=3, rando
```

In [105…

```
model.fit(X_train, y_train)
```

Out[105…

```
GradientBoostingClassifier(random_state=42)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [106…

```
train_predictions = model.predict(X_train)

train_accuracy9 = accuracy_score(y_train, train_predictions)
```

In [107…

```
test_predictions = model.predict(X_test)

test_accuracy9 = accuracy_score(y_test, test_predictions)
```

In [108…

```
print(f"Training Accuracy: {train_accuracy9}")
print(f"Testing Accuracy: {test_accuracy9}")
```

```
Training Accuracy: 0.889344262295082
Testing Accuracy: 0.7704918032786885
```

Random Forest, Decision Tree, Gradient Boosting Machines (GBM), Algorithm is the best accuracy

(GradientBoostingClassifier)

accuracy min = 8.5

10 | Hierarchical Clustering

In [109…

```
from scipy.cluster.hierarchy import linkage, dendrogram, fcluster
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
```

In [110…

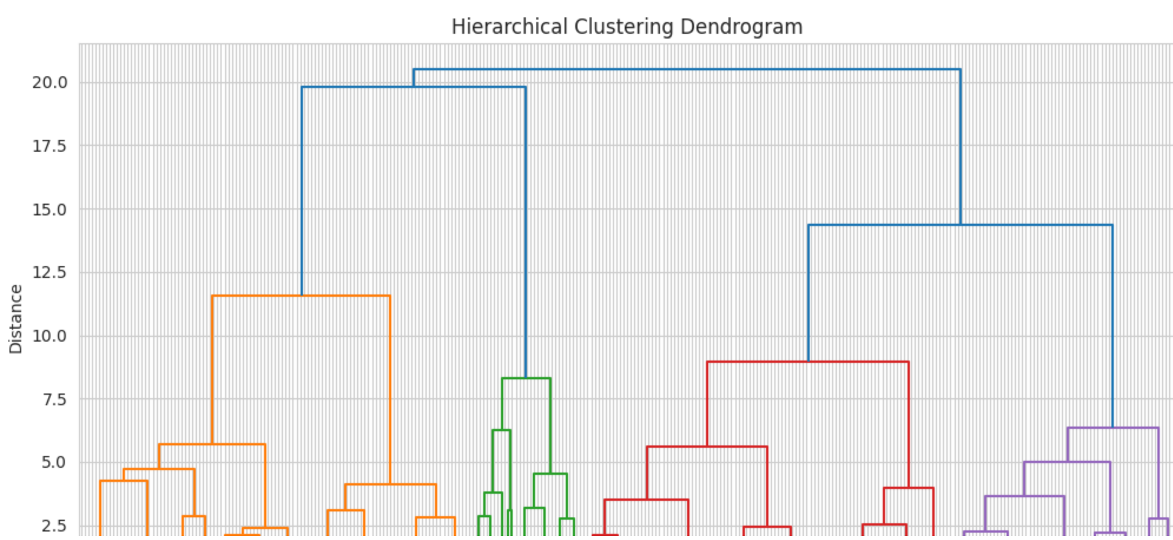
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [111…

```
linkage_matrix = linkage(X_scaled, method='ward')
```

In [114…

```
plt.figure(figsize=(12, 6))
dendrogram(linkage_matrix, labels=df['Status'].values, orientation='top', distance_sort='
plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('Status')
plt.ylabel('Distance')
plt.show()
```




0.0
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