In [1]:
```
import warnings
warnings.filterwarnings('ignore') #Ignoring the warning messages
import pandas as pd
import seaborn as sns
from sklearn. model_selection import train_test_split, GridSearchCV
from sklearn. linear_model import LogisticRegression
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
from sklearn. metrics import accuracy_score, precision_score, recall_score, f1_s
from sklearn.preprocessing import LabelEncoder, StandardScaler
```

In [2]:
```
# Loading the Titanic Data
datafile = pd.read_csv("I:\Applied ML\malhar\Titanic - HW2.csv", sep=",",encodin

# Loading the original datafile in a variable
df = datafile

#showing first 5 rows
df.head()
```

Out[2]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0

Question 1
Display the statistical values for each of the attributes, along with visualizations (e.g., histogram) of the distributions for

each attribute. Are there any attributes that might require special treatment? If so, what special treatment might they require?

In [3]:
```
print(f"Number of Rows: {df.shape[0]}")
print(f"Number of Columns: {df.shape[1]}")
```

```
Number of Rows: 891
Number of Columns: 12
```

In [4]:
```
df.describe()
```

Out[4]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.00(
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.00(
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.91(
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.00(
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329

In [5]:
```
# Obtaining the Data Info
df.info()
print("*"*100)
# Checking for NAs
df.isna().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
*********************************************************************************
*******************
```

Out[5]:

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

In [6]:

```
# Filling the NAs in Age column with the median age
df['Age'].fillna(df['Age'].median(), inplace = True)

# Filling the NAs in Embarked column with the first mode
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace = True)

# Removing not esential columns
df = df.drop(columns=['Name', 'Cabin', 'Ticket', 'PassengerId'])

df.info()
print("*"*100)
# Checking for NAs
df.isna().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Survived  891 non-null    int64
 1   Pclass    891 non-null    int64
 2   Sex       891 non-null    object
 3   Age       891 non-null    float64
 4   SibSp     891 non-null    int64
 5   Parch     891 non-null    int64
 6   Fare      891 non-null    float64
 7   Embarked  891 non-null    object
dtypes: float64(2), int64(4), object(2)
memory usage: 55.8+ KB
********************************************************************************
********************
```

Out[6]:

```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
```

In [7]:

```
# Converting 'Sex' & 'Embarked' to numerical category
df['Sex'].replace(['male', 'female'], [0,1], inplace = True)
df['Embarked'].replace(['S', 'C', 'Q'], [0, 1, 2], inplace = True)
print(df.head(5))
print("*"*100)
print(df.info())
print("*"*100)
print(df.isna().sum())
```

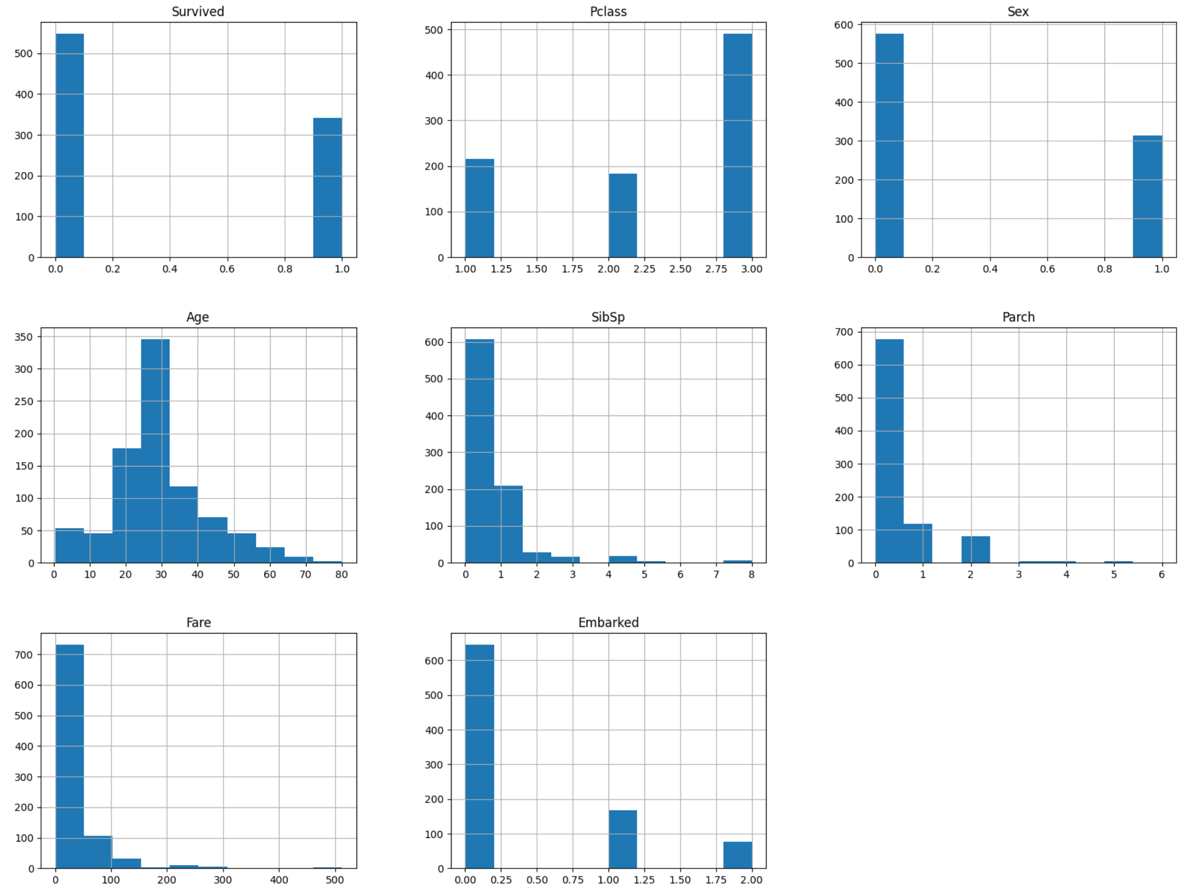
```
   Survived  Pclass  Sex   Age  SibSp  Parch     Fare  Embarked
0         0       3    0  22.0      1      0   7.2500         0
1         1       1    1  38.0      1      0  71.2833         1
2         1       3    1  26.0      0      0   7.9250         0
3         1       1    1  35.0      1      0  53.1000         0
4         0       3    0  35.0      0      0   8.0500         0
*********************************************************************************
*******************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Survived  891 non-null    int64  
 1   Pclass    891 non-null    int64  
 2   Sex       891 non-null    int64  
 3   Age       891 non-null    float64
 4   SibSp     891 non-null    int64  
 5   Parch     891 non-null    int64  
 6   Fare      891 non-null    float64
 7   Embarked  891 non-null    int64  
dtypes: float64(2), int64(6)
memory usage: 55.8 KB
None
*********************************************************************************
*******************
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
```

In [8]:

```
df.hist(grid=True,figsize=(20,15))
```

Out[8]:

```
array([[<Axes: title={'center': 'Survived'}>,
        <Axes: title={'center': 'Pclass'}>,
        <Axes: title={'center': 'Sex'}>],
       [<Axes: title={'center': 'Age'}>,
        <Axes: title={'center': 'SibSp'}>,
        <Axes: title={'center': 'Parch'}>],
       [<Axes: title={'center': 'Fare'}>,
        <Axes: title={'center': 'Embarked'}>, <Axes: >]], dtype=object)
```



Answer 1

1. There is special treatment required for 'Age' & 'Embarked' columns as this attributes had NA values for in them.
    - The NA values in 'Age' have been replaced by the median values for age
    - The NA values in 'Embarked' have been replaced by the mode values, as the mode will give the most frequent port of embarkment.
2. To determine whether or not a passenger survived, we do not need the cabin number, passenger name, or the ticket number, therefore the columns - 'Name', 'Cabin', 'Ticket' were removed.
3. 'Sex' & 'Embarked' columns have been converted to numerical format from a categorical format using the replace function.

Question 2
Analyze and discuss the relationships between the data attributes, and between the data attributes and label. This involves computing the Pearson

Correlation Coefficient (PCC) and generating scatter plots.

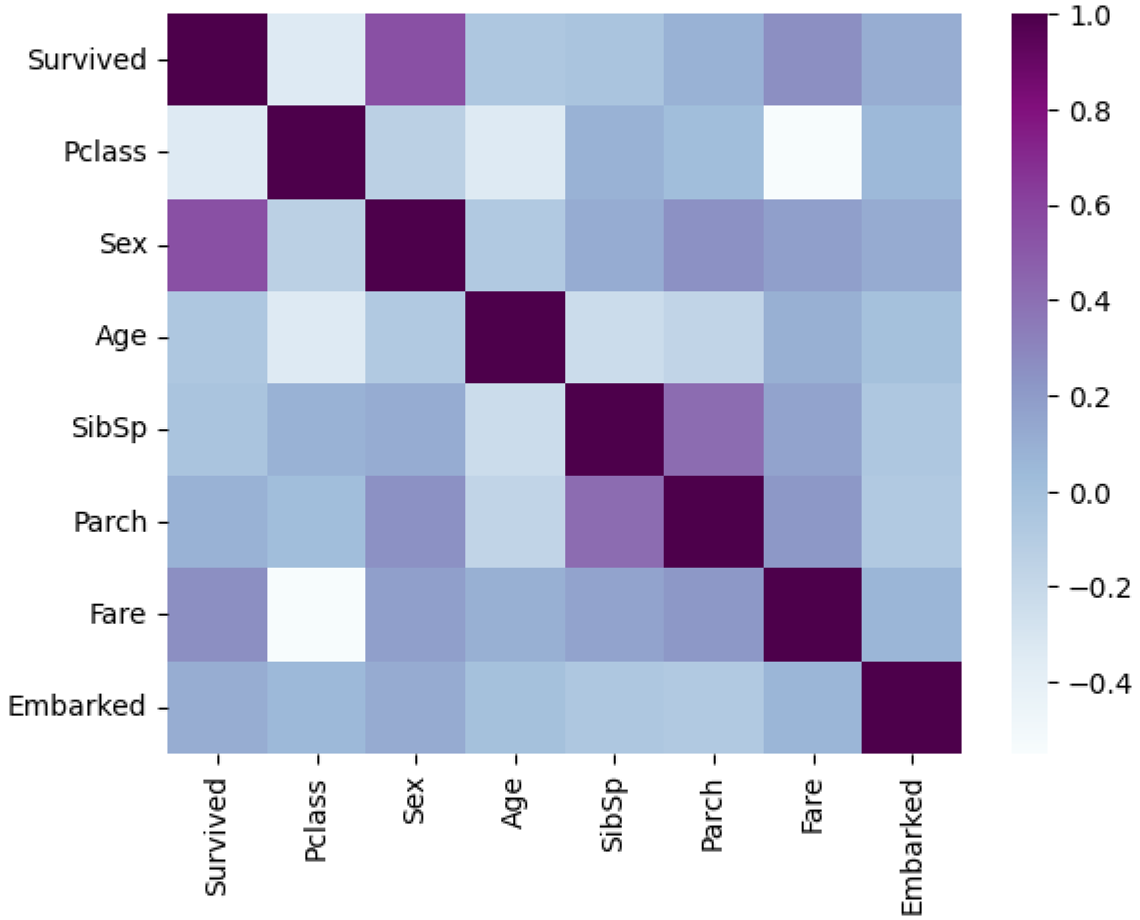
In [9]:
```
df.corr(method="pearson")
```

Out[9]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	E
Survived	1.000000	-0.338481	0.543351	-0.064910	-0.035322	0.081629	0.257307	
Pclass	-0.338481	1.000000	-0.131900	-0.339898	0.083081	0.018443	-0.549500	
Sex	0.543351	-0.131900	1.000000	-0.081163	0.114631	0.245489	0.182333	
Age	-0.064910	-0.339898	-0.081163	1.000000	-0.233296	-0.172482	0.096688	
SibSp	-0.035322	0.083081	0.114631	-0.233296	1.000000	0.414838	0.159651	
Parch	0.081629	0.018443	0.245489	-0.172482	0.414838	1.000000	0.216225	
Fare	0.257307	-0.549500	0.182333	0.096688	0.159651	0.216225	1.000000	
Embarked	0.106811	0.045702	0.116569	-0.009165	-0.059961	-0.078665	0.062142	

In [10]:
```
sns.heatmap(df.corr(method="pearson"), annot = False, cmap="BuPu")
```

Out[10]: <Axes: >



In [11]:
```
# Finding the Correlation for every attribute with the label - 'rock category'
for column in df:
```

```
    print(column,": ", df[column].corr(df['Survived']))
```

```
Survived :  1.0
Pclass :  -0.3384810359610148
Sex :  0.5433513806577546
Age :  -0.06491041993052583
SibSp :  -0.03532249888573557
Parch :  0.08162940708348361
Fare :  0.2573065223849622
Embarked :  0.10681138570891942
```

In [12]:
```
# Finding attributes that are positively correlated
pos_cols = []
print("The negatively Correlated Attributes are - ")
for column in df:
    if df[column].corr(df['Survived']) > 0:
        print("\t", column,": ", df[column].corr(df['Survived']))
        pos_cols.append(column)
```

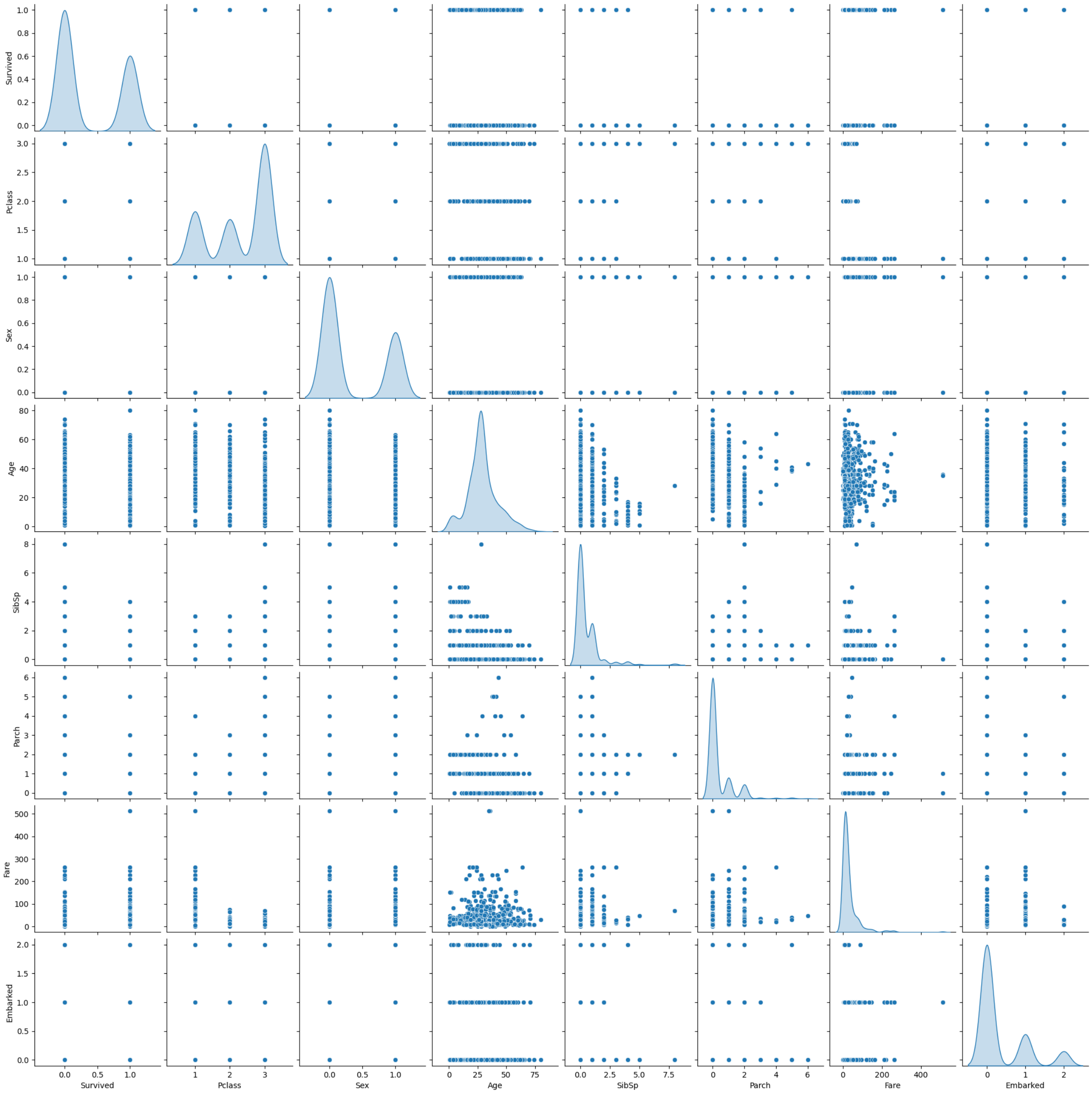
```
The negatively Correlated Attributes are - 
         Survived :  1.0
         Sex :  0.5433513806577546
         Parch :  0.08162940708348361
         Fare :  0.2573065223849622
         Embarked :  0.10681138570891942
```

In [13]:
```
# Finding attributes that are negatively correlated
neg_cols = []
print("The negatively Correlated Attributes are - ")
for column in df:
    if df[column].corr(df['Survived']) < 0:
        print("\t", column,": ", df[column].corr(df['Survived']))
        neg_cols.append(column)
```

```
The negatively Correlated Attributes are - 
         Pclass :  -0.3384810359610148
         Age :  -0.06491041993052583
         SibSp :  -0.03532249888573557
```

In [14]:
```
# Generating Scatter Plots
sns.pairplot(df, diag_kind="kde")
```

Out[14]: <seaborn.axisgrid.PairGrid at 0x1715e2715b0>



Answer 2

- The columns 'PClass', 'Age', 'Sibsp' are negatively correlated to the label - 'Survived'.
- The columsns 'Sex', 'Parch', 'Fare', 'Embarked' are positively correlated to the label - 'Survived'.

Question 3
Select 20% of the data for testing and 20% for validation and use the remaining 60% of the data for training. Describe how you did that and verify that your test and validation portions of the data are representative of the entire dataset.

In [15]:
```
# Splitting data into 60% training and 40% temp
X = df.drop(columns = ['Survived'])
y = df['Survived']
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.4, random_

# Splitting data into test & validation based of the 40% Temp data
# Splitting data into 50% testing and 50% validation
X_validation, X_test, y_validation, y_test = train_test_split(X_temp, y_temp, te
```

In [16]:
```
df.describe()
```

Out[16]:

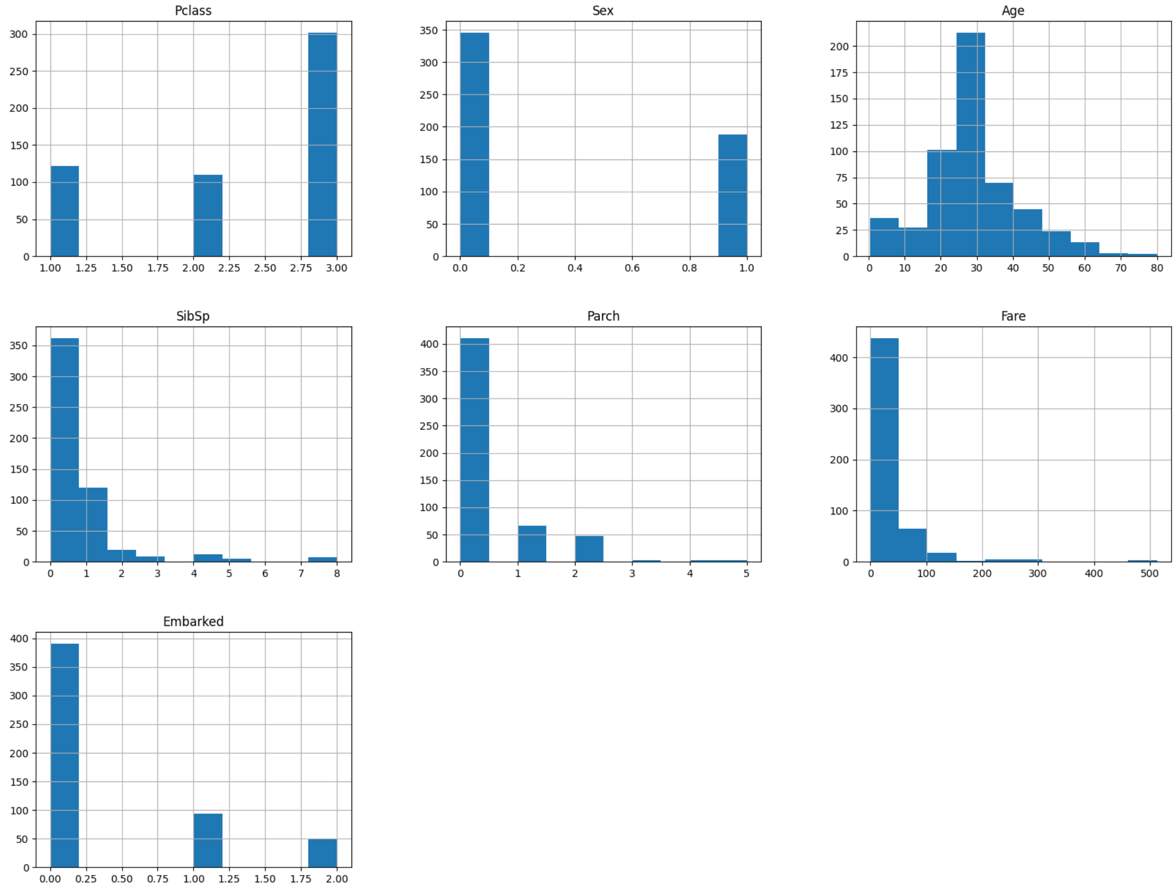
	Survived	Pclass	Sex	Age	SibSp	Parch	Fa
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.0000
mean	0.383838	2.308642	0.352413	29.361582	0.523008	0.381594	32.2042
std	0.486592	0.836071	0.477990	13.019697	1.102743	0.806057	49.6934
min	0.000000	1.000000	0.000000	0.420000	0.000000	0.000000	0.0000
25%	0.000000	2.000000	0.000000	22.000000	0.000000	0.000000	7.9104
50%	0.000000	3.000000	0.000000	28.000000	0.000000	0.000000	14.4542
75%	1.000000	3.000000	1.000000	35.000000	1.000000	0.000000	31.0000
max	1.000000	3.000000	1.000000	80.000000	8.000000	6.000000	512.3292

In [17]:
```
print(f"The shape of Training Set is: ", X_train.shape)
print(f"The shape of Training Set label is: ", y_train.shape)
print("*"*100)
print(f"The shape of Validation Set is: ", X_validation.shape)
print(f"The shape of Validation Set label is: ", y_validation.shape)
print("*"*100)
print(f"The shape of Testing Set is: ", X_test.shape)
print(f"The shape of Testing Set label is: ", y_test.shape)
print("*"*100)
```

```
The shape of Training Set is:  (534, 7)
The shape of Training Set label is:  (534,)
*********************************************************************************
*******************
The shape of Validation Set is:  (178, 7)
The shape of Validation Set label is:  (178,)
*********************************************************************************
*******************
The shape of Testing Set is:  (179, 7)
The shape of Testing Set label is:  (179,)
*********************************************************************************
*******************
```

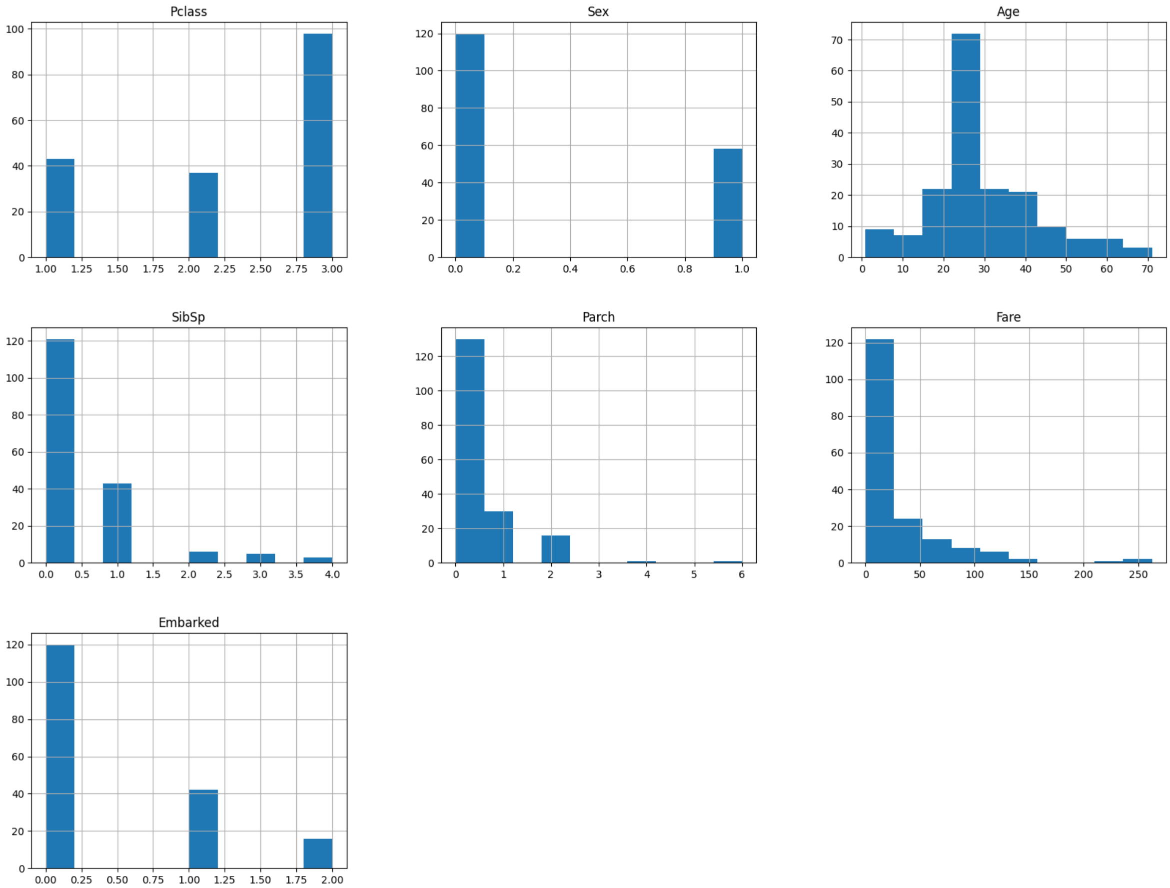
In [18]:
```
X_train.hist(grid=True,figsize=(20,15))
```

Out[18]:
```
array([[<Axes: title={'center': 'Pclass'}>,
        <Axes: title={'center': 'Sex'}>, <Axes: title={'center': 'Age'}>],
       [<Axes: title={'center': 'SibSp'}>,
        <Axes: title={'center': 'Parch'}>,
        <Axes: title={'center': 'Fare'}>],
       [<Axes: title={'center': 'Embarked'}>, <Axes: >, <Axes: >]],
      dtype=object)
```



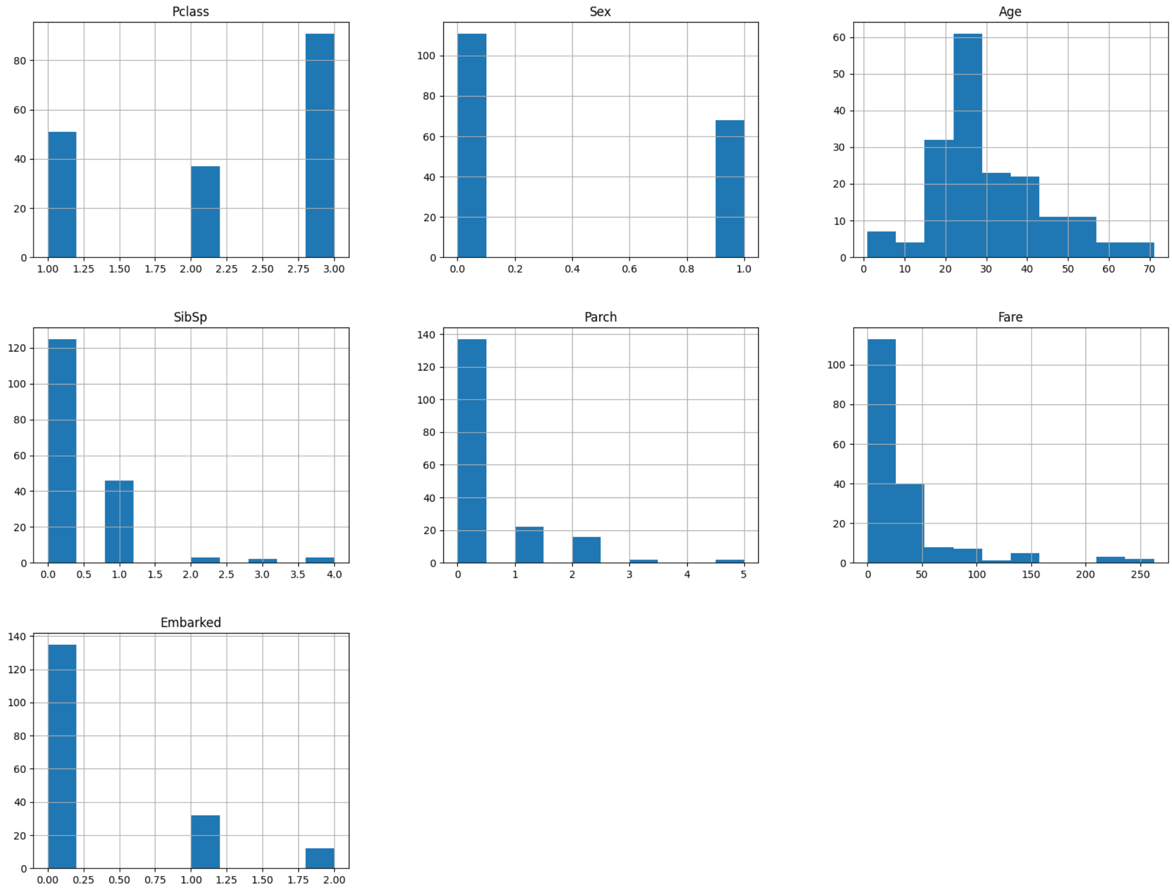
In [19]:
```python
X_validation.hist(grid=True,figsize=(20,15))
```

Out[19]:
```
array([[<Axes: title={'center': 'Pclass'}>,
        <Axes: title={'center': 'Sex'}>, <Axes: title={'center': 'Age'}>],
       [<Axes: title={'center': 'SibSp'}>,
        <Axes: title={'center': 'Parch'}>,
        <Axes: title={'center': 'Fare'}>],
       [<Axes: title={'center': 'Embarked'}>, <Axes: >, <Axes: >]],
      dtype=object)
```



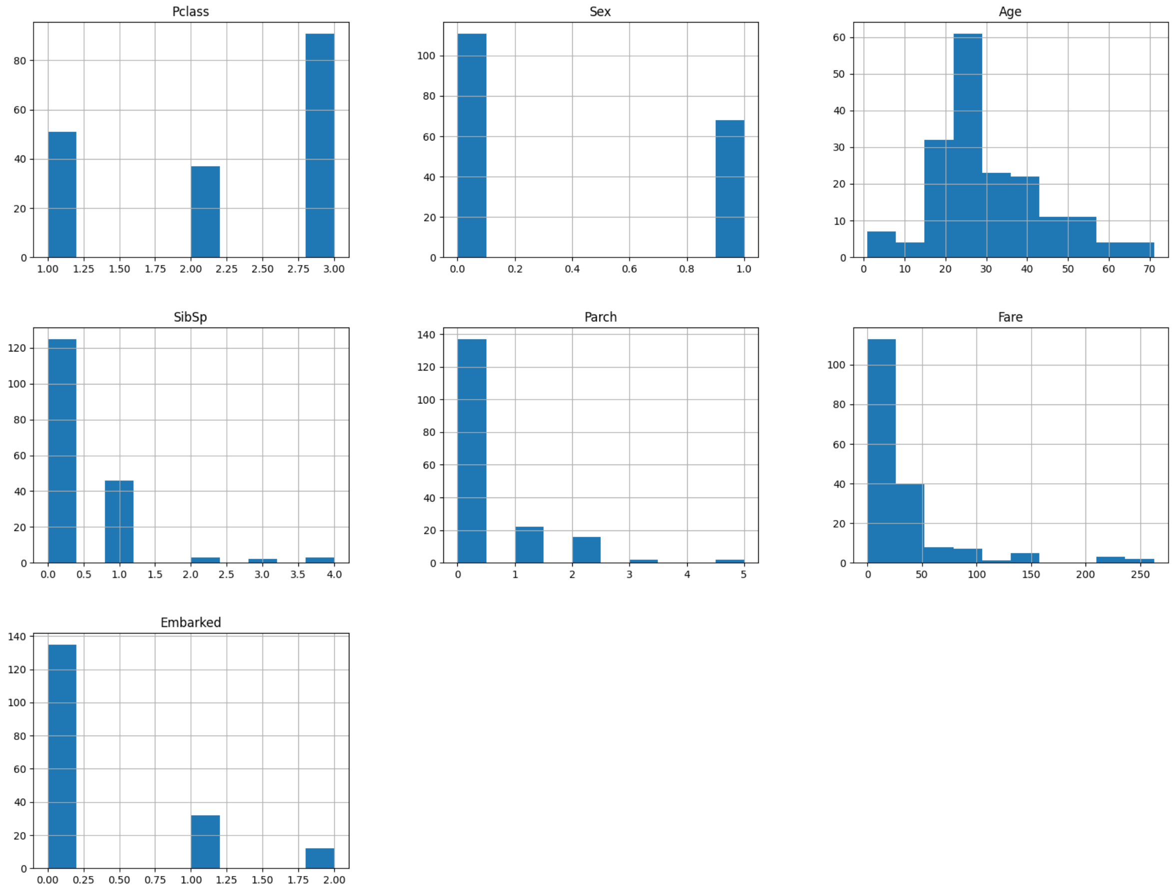
In [20]:
```
X_test.hist(grid=True,figsize=(20,15))
```

Out[20]:
```
array([[<Axes: title={'center': 'Pclass'}>,
        <Axes: title={'center': 'Sex'}>, <Axes: title={'center': 'Age'}>],
       [<Axes: title={'center': 'SibSp'}>,
        <Axes: title={'center': 'Parch'}>,
        <Axes: title={'center': 'Fare'}>],
       [<Axes: title={'center': 'Embarked'}>, <Axes: >, <Axes: >]],
      dtype=object)
```



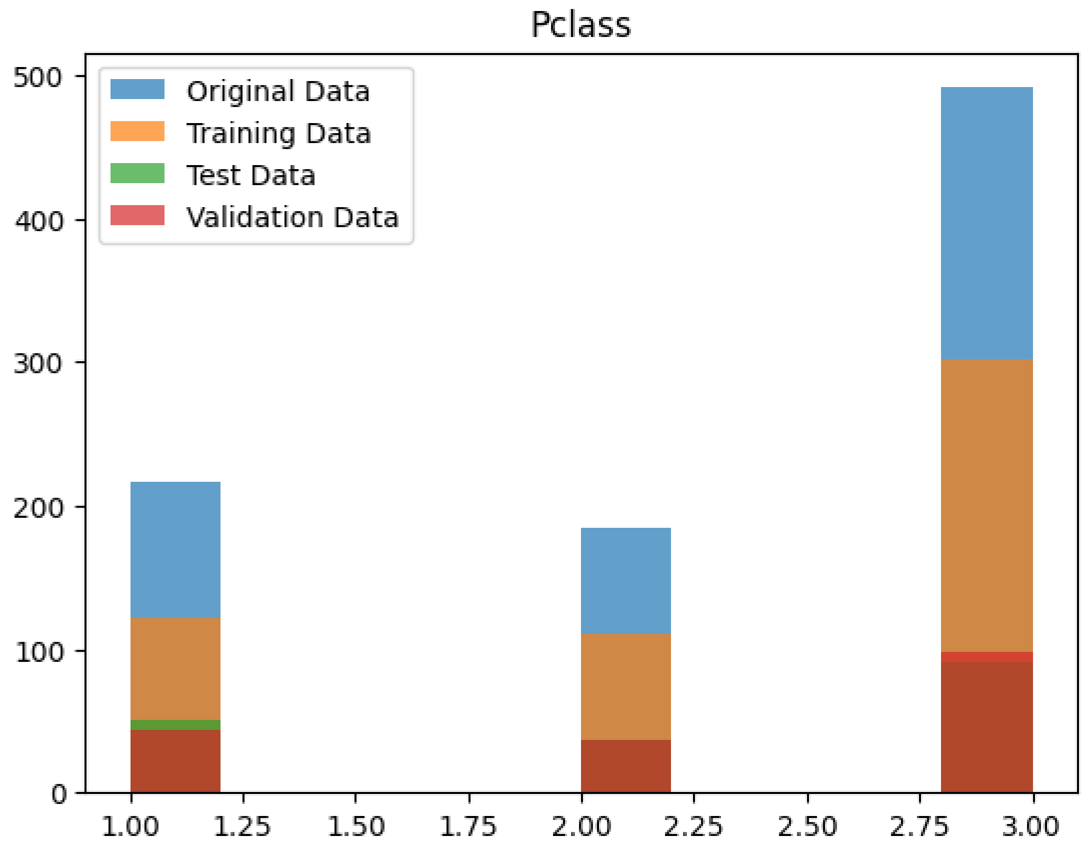
In [21]:
```
X_test.hist(grid=True,figsize=(20,15))
```

Out[21]:
```
array([[<Axes: title={'center': 'Pclass'}>,
        <Axes: title={'center': 'Sex'}>, <Axes: title={'center': 'Age'}>],
       [<Axes: title={'center': 'SibSp'}>,
        <Axes: title={'center': 'Parch'}>,
        <Axes: title={'center': 'Fare'}>],
       [<Axes: title={'center': 'Embarked'}>, <Axes: >, <Axes: >]],
      dtype=object)
```

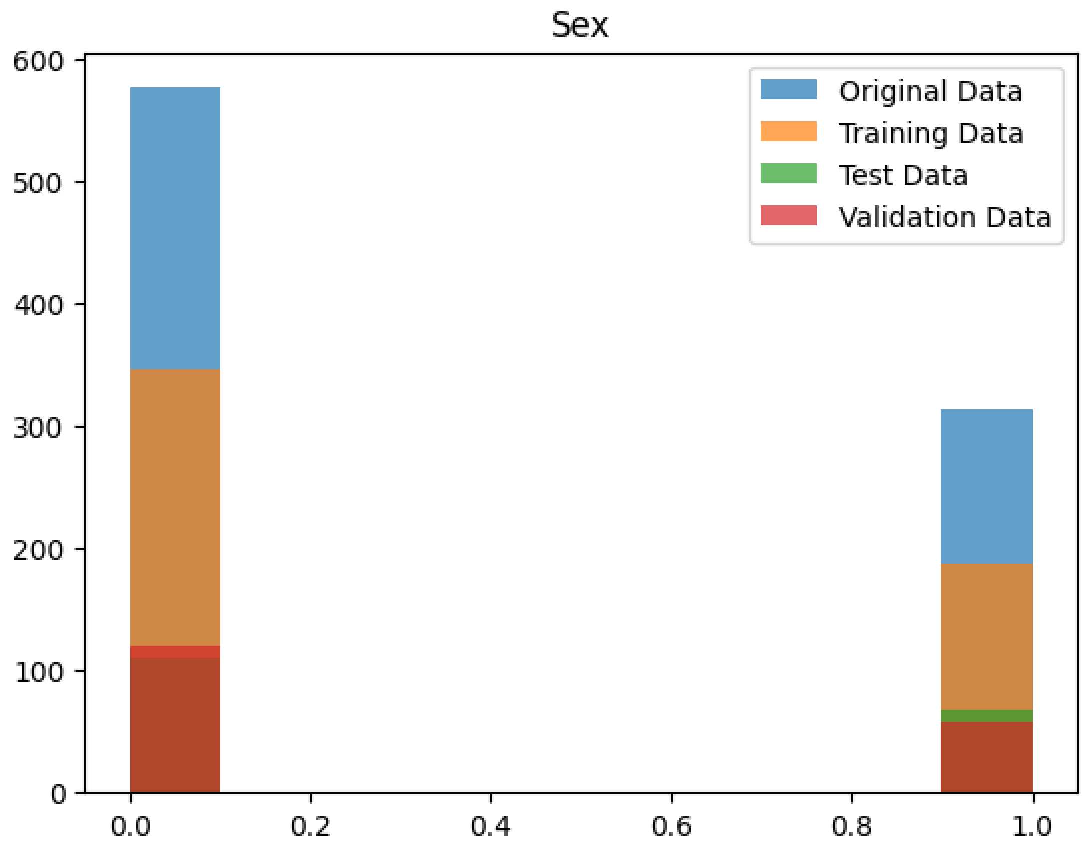


In [22]:

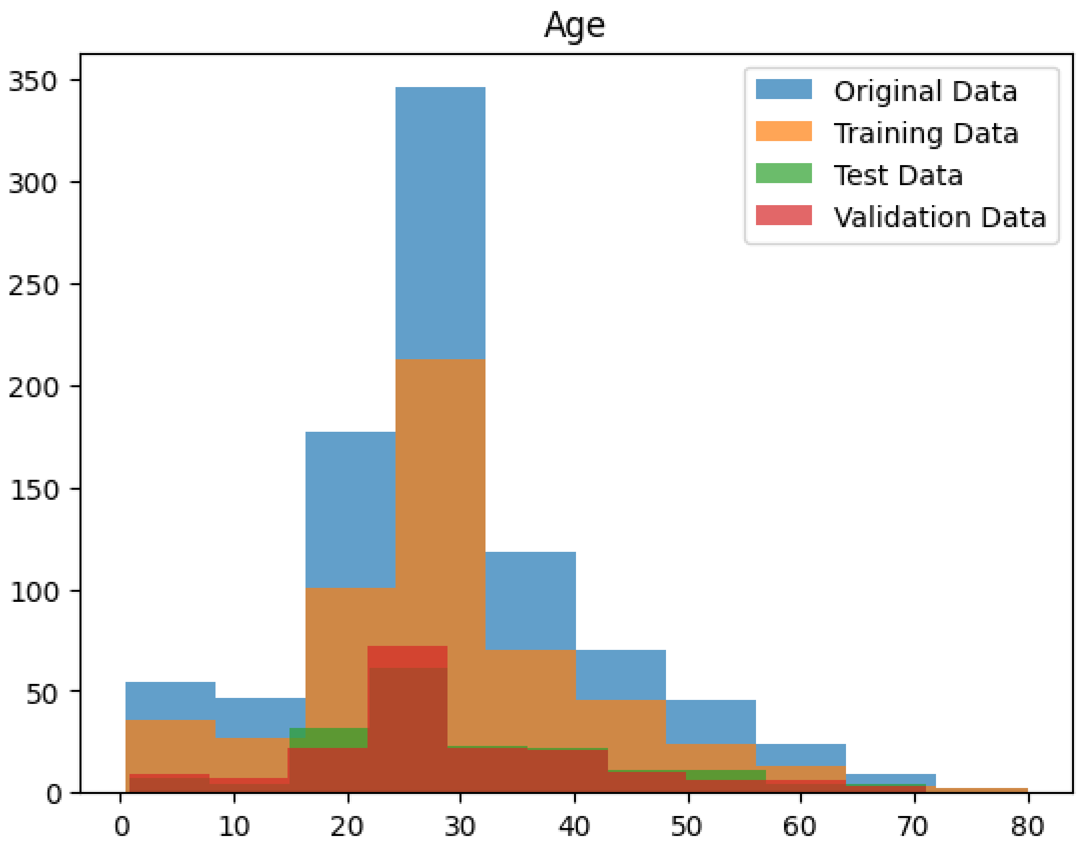
```
# Plotting every Column for Original, Test, Train & Validation data
# in order to verify whether the datasets are representative of the entire datas

for cols in X.columns:
    fig, ax = plt.subplots()
    ax.hist(X[cols], alpha = 0.7, label = "Original Data")
    ax.hist(X_train[cols], alpha = 0.7, label = "Training Data")
    ax.hist(X_test[cols], alpha = 0.7, label = "Test Data")
    ax.hist(X_validation[cols], alpha = 0.7, label = "Validation Data")
    ax.legend()
    plt.title(cols)
    plt.figure(figsize=(6,8))
```



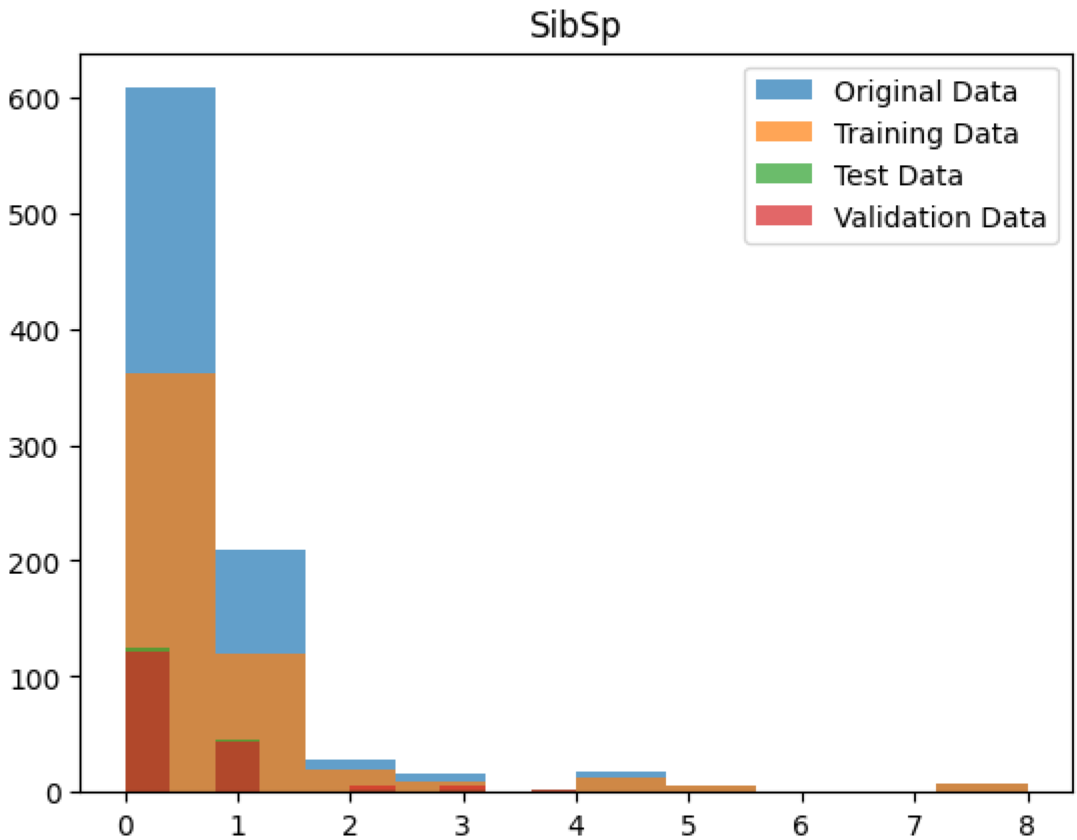

```
<Figure size 600x800 with 0 Axes>
```



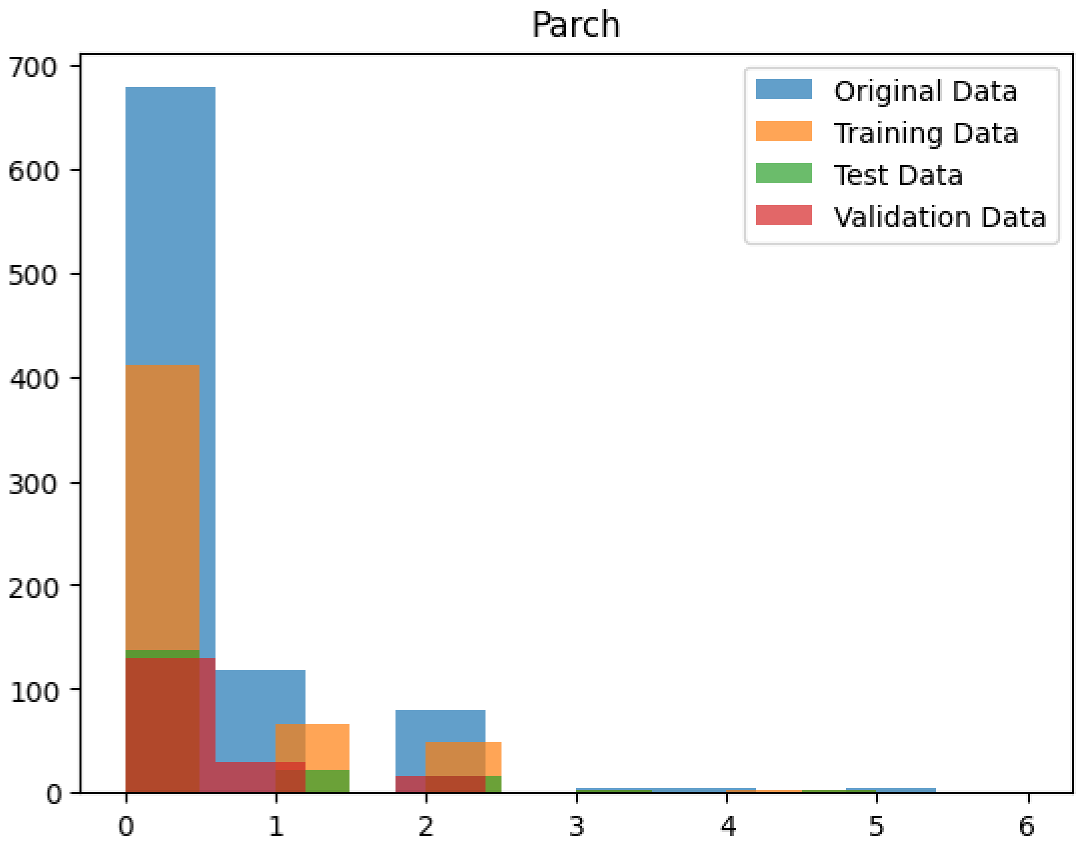

```
<Figure size 600x800 with 0 Axes>
```



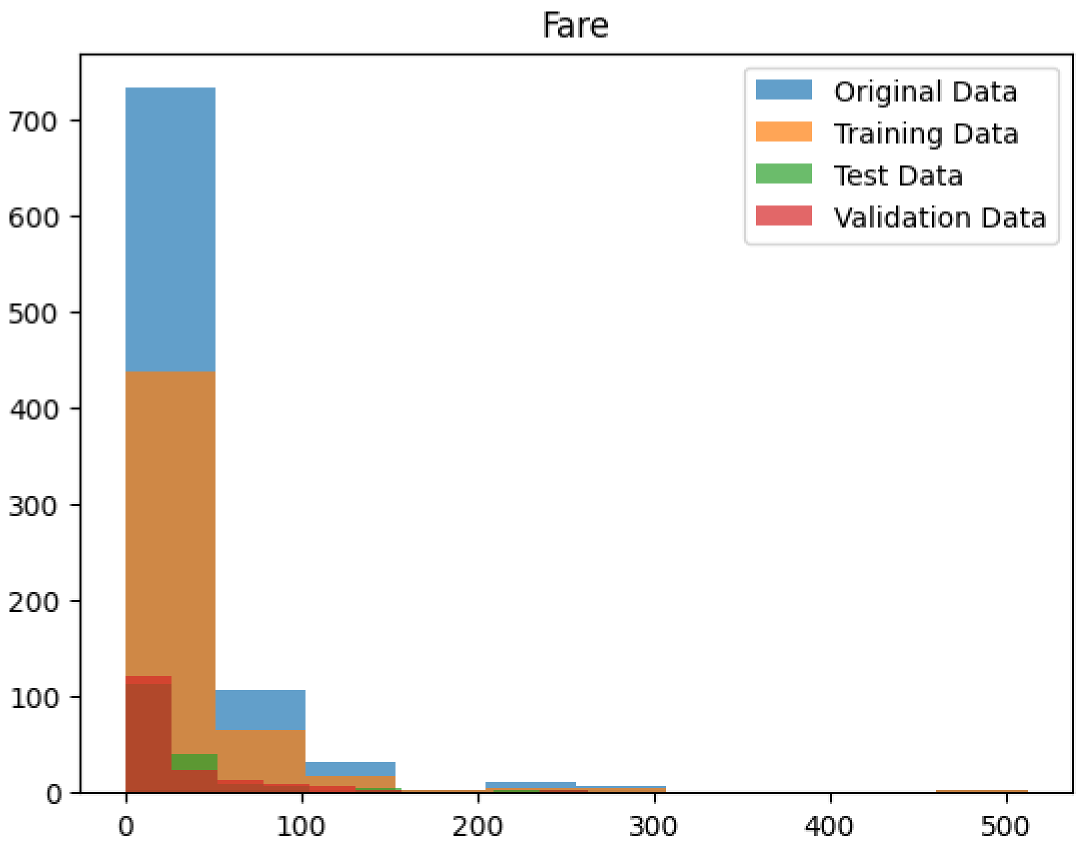

```
<Figure size 600x800 with 0 Axes>
```



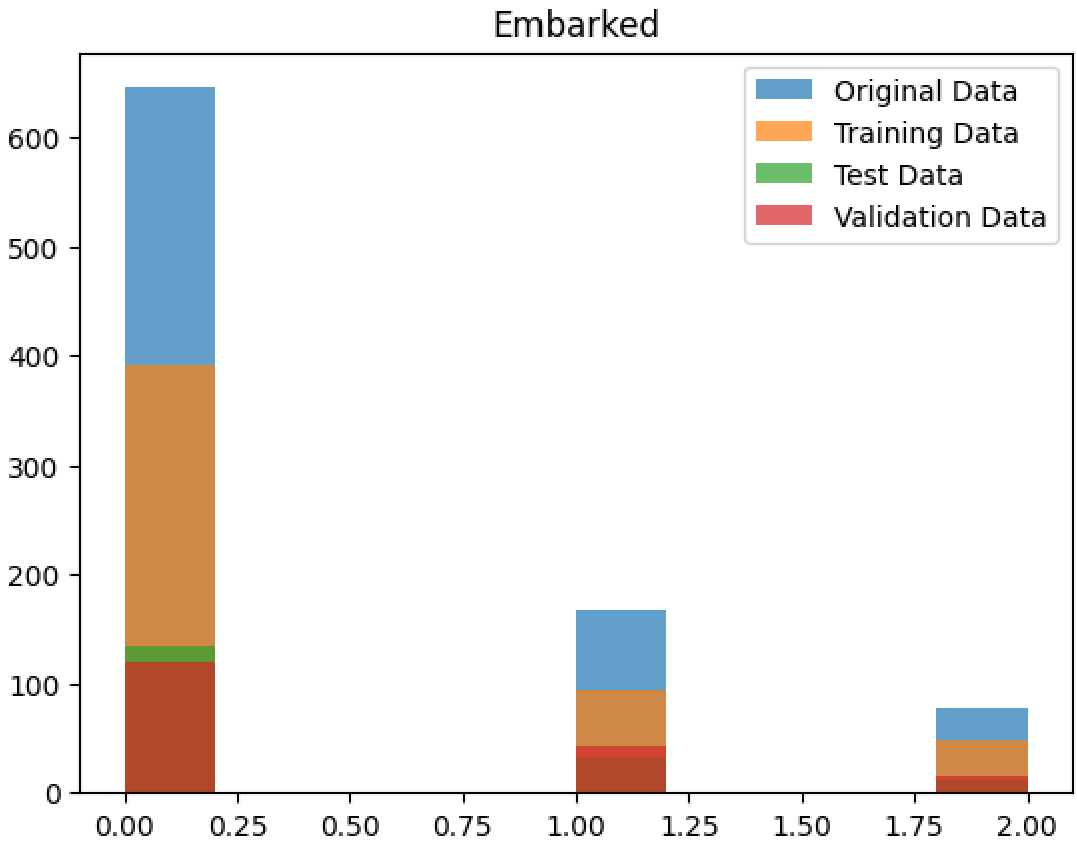

```
<Figure size 600x800 with 0 Axes>
```



<Figure size 600x800 with 0 Axes>



<Figure size 600x800 with 0 Axes>




```
<Figure size 600x800 with 0 Axes>
```

Answer 3

- The feature & lable data was divided into a 60%, 20% & 20% split for Trainig, Testing & Validating data respectively.
- We have plotted histograms for evey data set, to verify whether it represents the entire dataset.
- After plotting the datasets for each attribute in the train, test, validation & original dataset, we can verify that the training, testing & validation datasets are representative of the entire dataset.

Q.4 Train different classifiers and tweak the hyperparameters to improve performance (you can use the grid search if you want or manually try different values). Report training, validation and testing performance (classification accuracy, precision, recall and F1 score) and discuss the impact of the hyperparameters (use markdown cells in

Jupyter Notebook to clearly indicate each solution):

1. Multinomial Logistic Regression (softmax regression); hyperparameters to explore: C, solver, max number of iterations.
2. Support vector machines (make sure to try using kernels); hyperparameters to explore: C, kernel, degree of polynomial kernel, gamma.
3. Random Forest classifier (also analyze feature importance); hyperparameters to explore: the number of trees, max depth, the minimum number of samples required to split an internal node, the minimum number of samples required to be at a leaf node.

Multimonial Logistic regression

In [23]:

```
# Multimonial Logistic regression
# Implementing Grid search to find the best parameter combination
# Define hyperparameter grid
param_grid = {
    'penalty': ['l2', 'l1', 'elasticnet', 'none'],
    'C': [ 1.75, 2.0, 2.25, 2.50, 2.75, 3.0, 4.0, 5.0],  # Regularization parame
    'solver': ['lbfgs', 'sag', 'saga', 'newton-cholesky'],  # Optimization algor
    'max_iter': [500, 600, 800, 1000],  # Maximum number of iterations
}

# Create the logistic regression classifier
logistic_regression = LogisticRegression(multi_class='multinomial', random_state

# Looping different values of cv, to test the performace with the Validation dat
for i in range(2,8):

    # Grid search to find the best hyperparameters
    grid_search = GridSearchCV(logistic_regression, param_grid, cv = i, scoring
    grid_search.fit(X_train, y_train.values.ravel())

    # Get the best hyperparameters
    best_params = grid_search.best_params_
    print(f"For cv = ", i)
    print("The best parameter are: ", best_params)
    print("The accuracy score for the above parameters: ", grid_search.best_scor

    # Train the model with the best hyperparameters
    best_logistic_regression = LogisticRegression(multi_class='multinomial', ran
    best_logistic_regression.fit(X_train, y_train.values.ravel())

    # Validation set performance
```

```
    y_val_pred = best_logistic_regression.predict(X_validation)
    val_accuracy = accuracy_score(y_validation, y_val_pred)
    val_precision = precision_score(y_validation, y_val_pred, average='weighted'
    val_recall = recall_score(y_validation, y_val_pred, average='weighted')
    val_f1 = f1_score(y_validation, y_val_pred, average='weighted')

    # Print performance metrics
    print("Validation Metrics:")
    print(f"\tAccuracy: {val_accuracy:.4f}")
    print(f"\tPrecision: {val_precision:.4f}")
    print(f"\tRecall: {val_recall:.4f}")
    print(f"\tF1 Score: {val_f1:.4f}")
    print("*"*100)
```

```
For cv =  2
The best parameter are:  {'C': 1.75, 'max_iter': 500, 'penalty': 'l2', 'solver':
'lbfgs'}
The accuracy score for the above parameters:  0.7958801498127341
Validation Metrics:
        Accuracy: 0.7697
        Precision: 0.7667
        Recall: 0.7697
        F1 Score: 0.7675
*********************************************************************************
*******************
For cv =  3
The best parameter are:  {'C': 1.75, 'max_iter': 500, 'penalty': 'l2', 'solver':
'lbfgs'}
The accuracy score for the above parameters:  0.8108614232209738
Validation Metrics:
        Accuracy: 0.7697
        Precision: 0.7667
        Recall: 0.7697
        F1 Score: 0.7675
*********************************************************************************
*******************
For cv =  4
The best parameter are:  {'C': 1.75, 'max_iter': 500, 'penalty': 'l2', 'solver':
'lbfgs'}
The accuracy score for the above parameters:  0.8033189316575019
Validation Metrics:
        Accuracy: 0.7697
        Precision: 0.7667
        Recall: 0.7697
        F1 Score: 0.7675
*********************************************************************************
*******************
For cv =  5
The best parameter are:  {'C': 1.75, 'max_iter': 500, 'penalty': 'none', 'solve
r': 'lbfgs'}
The accuracy score for the above parameters:  0.7997354963851173
Validation Metrics:
        Accuracy: 0.7640
        Precision: 0.7615
        Recall: 0.7640
        F1 Score: 0.7624
*********************************************************************************
*******************
For cv =  6
The best parameter are:  {'C': 1.75, 'max_iter': 500, 'penalty': 'l2', 'solver':
'lbfgs'}
The accuracy score for the above parameters:  0.799625468164794
Validation Metrics:
        Accuracy: 0.7697
        Precision: 0.7667
        Recall: 0.7697
        F1 Score: 0.7675
*********************************************************************************
*******************
For cv =  7
The best parameter are:  {'C': 1.75, 'max_iter': 500, 'penalty': 'none', 'solve
r': 'lbfgs'}
The accuracy score for the above parameters:  0.8069524460501905
Validation Metrics:
```

```
        Accuracy: 0.7640
        Precision: 0.7615
        Recall: 0.7640
        F1 Score: 0.7624
********************************************************************************
*******************
```

- **From the above it can be seen that the Accuracy score for the model is not really changing for different the CV scores, but the model accuracy is the higgest when cv = 4, and the parameters are**
    - **{'C': 1.75, 'max_iter': 500, 'penalty': 'l2', 'solver': 'lbfgs'}.**
- **Therefore, using the above parameters as reference, the model is finalized by tuning the hyper parameters below -**

In [24]:
```python
# Finalizing the Multinomial Logistic Regression classifier
# Train the model with the best hyperparameters
final_logistic_regression = LogisticRegression(multi_class='multinomial', C = 6,
                                              random_state=42)
final_logistic_regression.fit(X_train, y_train.values.ravel())

# Training Data Performance
y_train_pred = final_logistic_regression.predict(X_train)
val_accuracy = accuracy_score(y_train, y_train_pred)
val_precision = precision_score(y_train, y_train_pred, average='weighted')
val_recall = recall_score(y_train, y_train_pred, average='weighted')
val_f1 = f1_score(y_train, y_train_pred, average='weighted')

# Print Training performance metrics
print("Validation Metrics:")
print(f"\tAccuracy: {val_accuracy:.4f}")
print(f"\tPrecision: {val_precision:.4f}")
print(f"\tRecall: {val_recall:.4f}")
print(f"\tF1 Score: {val_f1:.4f}")

# Validation set performance
y_val_pred = final_logistic_regression.predict(X_validation)
val_accuracy = accuracy_score(y_validation, y_val_pred)
val_precision = precision_score(y_validation, y_val_pred, average='weighted')
val_recall = recall_score(y_validation, y_val_pred, average='weighted')
val_f1 = f1_score(y_validation, y_val_pred, average='weighted')

# Print performance metrics
print("\nValidation Metrics:")
print(f"\tAccuracy: {val_accuracy:.4f}")
print(f"\tPrecision: {val_precision:.4f}")
print(f"\tRecall: {val_recall:.4f}")
print(f"\tF1 Score: {val_f1:.4f}")

# Test set performance
y_test_pred = final_logistic_regression.predict(X_test)
test_accuracy = accuracy_score(y_test, y_test_pred)
test_precision = precision_score(y_test, y_test_pred, average='weighted')
test_recall = recall_score(y_test, y_test_pred, average='weighted')
```

```
test_f1 = f1_score(y_test, y_test_pred, average='weighted')

# Print performance metrics
print("\nTest Metrics:")
print(f"\tAccuracy: {test_accuracy:.4f}")
print(f"\tPrecision: {test_precision:.4f}")
print(f"\tRecall: {test_recall:.4f}")
print(f"\tF1 Score: {test_f1:.4f}")
```

```
Validation Metrics:
        Accuracy: 0.8034
        Precision: 0.8014
        Recall: 0.8034
        F1 Score: 0.8017

Validation Metrics:
        Accuracy: 0.7640
        Precision: 0.7615
        Recall: 0.7640
        F1 Score: 0.7624

Test Metrics:
        Accuracy: 0.8212
        Precision: 0.8236
        Recall: 0.8212
        F1 Score: 0.8185
```

Compare to the Grid Search parameters -

1. The Accuracy of the model does not increase significantly for any change in the hyper parameters.
2. But the model gives a slightly better accuracy when C = 6
3. Therefore, the Multinomial Logistic Regression was finalized based on the following hyper parameters -
   - {'C': 6, 'max_iter': 1000, 'penalty' = 'l2', 'solver': 'lbfgs'}

Support Vector Machines

In [25]:

```
from sklearn.svm import SVC

# Define hyperparameter grid & Running only 'rbf' kernal
param_grid = {
    'C': [1.0, 1.5, 1.75, 2.0, 3.0, 4.0, 4.5, 5.0],  # Regularization parameter
    'kernel': ['rbf'],  # Kernel type
    'degree': [2, 3, 4],  # Degree of polynomial kernel (if applicable)
    'gamma': ['scale', 'auto', 0.001, 0.01, 0.1, 1, 2, 3, 4],  # Kernel coeffici
}

# Create the SVM classifier
svm_classifier = SVC(random_state=42,probability=True)

# Running a for Loop to find the best cv
for j in range(2,6):
    # Grid search to find the best hyperparameters
    grid_search_svm = GridSearchCV(svm_classifier, param_grid, cv = j, scoring =
    grid_search_svm.fit(X_train, y_train)
```

```
    # Get the best hyperparameters
    best_params_svm = grid_search_svm.best_params_
    print(f"For cv = ", j)
    print("The Best parameter combination is: ", best_params_svm)
    print("The accuracy score for the above parameters: ", grid_search_svm.best_

    # Train the model with the best hyperparameters
    best_svm_classifier = SVC(random_state=42, **best_params_svm,probability=Tru
    best_svm_classifier.fit(X_train, y_train.values.ravel())

    # Validation set performance
    y_val_pred = best_svm_classifier.predict(X_validation)
    val_accuracy = accuracy_score(y_validation, y_val_pred)
    val_precision = precision_score(y_validation, y_val_pred, average='weighted'
    val_recall = recall_score(y_validation, y_val_pred, average='weighted')
    val_f1 = f1_score(y_validation, y_val_pred, average='weighted')

    # Print performance metrics
    print("Validation Metrics:")
    print(f"\tAccuracy: {val_accuracy:.4f}")
    print(f"\tPrecision: {val_precision:.4f}")
    print(f"\tRecall: {val_recall:.4f}")
    print(f"\tF1 Score: {val_f1:.4f}")
    print("*"*100)
```

```
For cv =  2
The Best parameter combination is:  {'C': 4.5, 'degree': 2, 'gamma': 0.01, 'kerne
l': 'rbf'}
The accuracy score for the above parameters:  0.6872659176029963
Validation Metrics:
        Accuracy: 0.7416
        Precision: 0.7356
        Recall: 0.7416
        F1 Score: 0.7349
*********************************************************************************
*******************
For cv =  3
The Best parameter combination is:  {'C': 5.0, 'degree': 2, 'gamma': 0.01, 'kerne
l': 'rbf'}
The accuracy score for the above parameters:  0.6966292134831461
Validation Metrics:
        Accuracy: 0.7303
        Precision: 0.7233
        Recall: 0.7303
        F1 Score: 0.7219
*********************************************************************************
*******************
For cv =  4
The Best parameter combination is:  {'C': 4.5, 'degree': 2, 'gamma': 0.01, 'kerne
l': 'rbf'}
The accuracy score for the above parameters:  0.7059533161261363
Validation Metrics:
        Accuracy: 0.7416
        Precision: 0.7356
        Recall: 0.7416
        F1 Score: 0.7349
*********************************************************************************
*******************
For cv =  5
The Best parameter combination is:  {'C': 5.0, 'degree': 2, 'gamma': 0.01, 'kerne
l': 'rbf'}
The accuracy score for the above parameters:  0.7266090636572033
Validation Metrics:
        Accuracy: 0.7303
        Precision: 0.7233
        Recall: 0.7303
        F1 Score: 0.7219
*********************************************************************************
*******************
```

For 'rbf' Kernel

- **From the above simulation it can be seen that the Accuracy for the Validatioin Data doesn't really inmprove with the change in cv. But the best performing model produces an accuracy of 0.7266090636572033 when cv is 5.**
- **Therefore the above cv is the best for which the best hyperparameter combination is**
    - **{'C': 5.0, 'degree': 2, 'gamma': 0.01, 'kernel': 'rbf'}**
- **The best Validation Accuracy produced by this model is - 0.7303**

- **Based on the parameters above the 'rbf' model could be finalized below -**

In [26]:
```
from sklearn.svm import SVC

# Finalizing the SVM classifier for 'rbf' kernel
svm_classifier_rbf = SVC(random_state=42, probability=True, C = 5, kernel = 'rbf
svm_classifier_rbf.fit(X_train, y_train.values.ravel())

# Validation set performance
y_val_pred = svm_classifier_rbf.predict(X_validation)
val_accuracy = accuracy_score(y_validation, y_val_pred)
val_precision = precision_score(y_validation, y_val_pred, average='weighted')
val_recall = recall_score(y_validation, y_val_pred, average='weighted')
val_f1 = f1_score(y_validation, y_val_pred, average='weighted')

# Print performance metrics
print("Validation Metrics:")
print(f"\tAccuracy: {val_accuracy:.4f}")
print(f"\tPrecision: {val_precision:.4f}")
print(f"\tRecall: {val_recall:.4f}")
print(f"\tF1 Score: {val_f1:.4f}")

# Test set performance
y_test_pred = svm_classifier_rbf.predict(X_test)
test_accuracy = accuracy_score(y_test, y_test_pred)
test_precision = precision_score(y_test, y_test_pred, average='weighted')
test_recall = recall_score(y_test, y_test_pred, average='weighted')
test_f1 = f1_score(y_test, y_test_pred, average='weighted')

# Print performance metrics
print("\nTest Metrics:")
print(f"\tAccuracy: {test_accuracy:.4f}")
print(f"\tPrecision: {test_precision:.4f}")
print(f"\tRecall: {test_recall:.4f}")
print(f"\tF1 Score: {test_f1:.4f}")
```

```
Validation Metrics:
	Accuracy: 0.7528
	Precision: 0.7590
	Recall: 0.7528
	F1 Score: 0.7325

Test Metrics:
	Accuracy: 0.6872
	Precision: 0.7076
	Recall: 0.6872
	F1 Score: 0.6594
```

Compared to the Grid Search -

1. **After changing the hyper parameters there is no significant increase in Accuracy after changing the C or degree.**
2. **The Model performs slightly better when the following parameters are used -**
3. **Therefore, the following hyperparameters are optimum for SVM using 'rbf' kernel -**

- {'C': 5, 'degree': 2, 'gamma': 0.001, 'kernel': 'rbf'}

In [27]:
```
from sklearn.svm import SVC

# Define hyperparameter grid & Running only 'sigmoid' kernal
param_grid = {
    'C': [1.0, 1.5, 1.75, 2.0, 3.0, 4.0, 4.5, 5.0],  # Regularization parameter
    'kernel': ['sigmoid'],  # Kernel type
    'degree': [2, 3, 4],  # Degree of polynomial kernel (if applicable)
    'gamma': ['scale', 'auto', 0.001, 0.01, 0.1, 1, 2, 3, 4],  # Kernel coeffici
}

# Create the SVM classifier
svm_classifier = SVC(random_state=42,probability=True)

# Running a for loop to find the best cv
for j in range(2,6):
    # Grid search to find the best hyperparameters
    grid_search_svm = GridSearchCV(svm_classifier, param_grid, cv = j, scoring =
    grid_search_svm.fit(X_train, y_train)

    # Get the best hyperparameters
    best_params_svm = grid_search_svm.best_params_
    print(f"For cv = ", j)
    print("The Best parameter combination is: ", best_params_svm)
    print("The accuracy score for the above parameters: ", grid_search_svm.best_

    # Train the model with the best hyperparameters
    best_svm_classifier = SVC(random_state=42, **best_params_svm,probability=Tru
    best_svm_classifier.fit(X_train, y_train.values.ravel())

    # Validation set performance
    y_val_pred = best_svm_classifier.predict(X_validation)
    val_accuracy = accuracy_score(y_validation, y_val_pred)
    val_precision = precision_score(y_validation, y_val_pred, average='weighted'
    val_recall = recall_score(y_validation, y_val_pred, average='weighted')
    val_f1 = f1_score(y_validation, y_val_pred, average='weighted')

    # Print performance metrics
    print("Validation Metrics:")
    print(f"\tAccuracy: {val_accuracy:.4f}")
    print(f"\tPrecision: {val_precision:.4f}")
    print(f"\tRecall: {val_recall:.4f}")
    print(f"\tF1 Score: {val_f1:.4f}")
    print("*"*100)
```

```
For cv =  2
The Best parameter combination is:  {'C': 1.5, 'degree': 2, 'gamma': 0.01, 'kerne
l': 'sigmoid'}
The accuracy score for the above parameters:  0.6367041198501873
Validation Metrics:
        Accuracy: 0.6517
        Precision: 0.7031
        Recall: 0.6517
        F1 Score: 0.5389
*********************************************************************************
*******************
For cv =  3
The Best parameter combination is:  {'C': 1.0, 'degree': 2, 'gamma': 0.01, 'kerne
l': 'sigmoid'}
The accuracy score for the above parameters:  0.644194756554307
Validation Metrics:
        Accuracy: 0.6517
        Precision: 0.7031
        Recall: 0.6517
        F1 Score: 0.5389
*********************************************************************************
*******************
For cv =  4
The Best parameter combination is:  {'C': 1.0, 'degree': 2, 'gamma': 0.01, 'kerne
l': 'sigmoid'}
The accuracy score for the above parameters:  0.636670968465941
Validation Metrics:
        Accuracy: 0.6517
        Precision: 0.7031
        Recall: 0.6517
        F1 Score: 0.5389
*********************************************************************************
*******************
For cv =  5
The Best parameter combination is:  {'C': 3.0, 'degree': 2, 'gamma': 0.01, 'kerne
l': 'sigmoid'}
The accuracy score for the above parameters:  0.6442602715570445
Validation Metrics:
        Accuracy: 0.6629
        Precision: 0.7288
        Recall: 0.6629
        F1 Score: 0.5616
*********************************************************************************
*******************
```

For 'sigmoid' Kernel

- **From the above loop it can be seen that the Accuracy for the Validatioin Data doesn't really inmprove with the change in cv. But the best performing model produces an accuracy of 0.6310879915358842 when cv is 5.**
- **Therefore the above cv is the best for which the best hyperparameter combination is - {'C': 1.0, 'degree': 2, 'gamma': 0.001, 'kernel': 'sigmoid'}**
- **The best Validation Accuracy produced by this model is - 0.6292**

- **Based on the above hyper parameters the 'sigmoid' kernel could be finalized below -**

In [28]:
```
from sklearn.svm import SVC

# Finalizing the SVM classifier for 'rbf' kernel
svm_classifier_sig = SVC(random_state=42, probability=True, C = 3, kernel = 'sig
svm_classifier_sig.fit(X_train, y_train.values.ravel())

# Validation set performance
y_val_pred = svm_classifier_sig.predict(X_validation)
val_accuracy = accuracy_score(y_validation, y_val_pred)
val_precision = precision_score(y_validation, y_val_pred, average='weighted')
val_recall = recall_score(y_validation, y_val_pred, average='weighted')
val_f1 = f1_score(y_validation, y_val_pred, average='weighted')

# Print performance metrics
print("Validation Metrics:")
print(f"\tAccuracy: {val_accuracy:.4f}")
print(f"\tPrecision: {val_precision:.4f}")
print(f"\tRecall: {val_recall:.4f}")
print(f"\tF1 Score: {val_f1:.4f}")

# Test set performance
y_test_pred = svm_classifier_rbf.predict(X_test)
test_accuracy = accuracy_score(y_test, y_test_pred)
test_precision = precision_score(y_test, y_test_pred, average='weighted')
test_recall = recall_score(y_test, y_test_pred, average='weighted')
test_f1 = f1_score(y_test, y_test_pred, average='weighted')

# Print performance metrics
print("\nTest Metrics:")
print(f"\tAccuracy: {test_accuracy:.4f}")
print(f"\tPrecision: {test_precision:.4f}")
print(f"\tRecall: {test_recall:.4f}")
print(f"\tF1 Score: {test_f1:.4f}")
```

```
Validation Metrics:
        Accuracy: 0.6629
        Precision: 0.7288
        Recall: 0.6629
        F1 Score: 0.5616

Test Metrics:
        Accuracy: 0.6872
        Precision: 0.7076
        Recall: 0.6872
        F1 Score: 0.6594
```

Compared to the Grid Search -

1. **After changing the hyper parameters there is no significant increase in Accuracy after changing the degree, or gamma.**
2. **The Model performs slightly better when C = 3.**
3. **Therefore, the following hyperparameters are the optimum for SVM using 'sigmoid' kernel -**

- # {'C': 3, 'degree': 2, 'gamma': 'scale', 'kernel': 'sigmoid'}

In [29]:
```
# from sklearn.svm import SVC

# # Define hyperparameter grid & Running only 'linear' kernal
# param_grid = {
#     'C': [1.0, 1.5, 1.75, 2.0, 3.0, 4.0, 4.5, 5.0],  # Regularization paramete
#     'kernel': ['linear'],  # Kernel type
#     'gamma': ['scale', 'auto', 0.001, 0.01, 0.1, 1, 2, 3, 4],  # Kernel coeffi
# }

# # Create the SVM classifier
# svm_classifier = SVC(random_state=42,probability=True)

# # Running a for loop to find the best cv
# for j in range(2,9):
#     # Grid search to find the best hyperparameters
#     grid_search_svm = GridSearchCV(svm_classifier, param_grid, cv = j, scoring
#     grid_search_svm.fit(X_train, y_train)

#     # Get the best hyperparameters
#     best_params_svm = grid_search_svm.best_params_
#     print(f"For cv = ", j)
#     print("The Best parameter combination is: ", best_params_svm)
#     print("The accuracy score for the above parameters: ", grid_search_svm.bes

#     # Train the model with the best hyperparameters
#     best_svm_classifier = SVC(random_state=42, **best_params_svm,probability=T
#     best_svm_classifier.fit(X_train, y_train.values.ravel())

#     # Validation set performance
#     y_val_pred = best_svm_classifier.predict(X_validation)
#     val_accuracy = accuracy_score(y_validation, y_val_pred)
#     val_precision = precision_score(y_validation, y_val_pred, average='weighte
#     val_recall = recall_score(y_validation, y_val_pred, average='weighted')
#     val_f1 = f1_score(y_validation, y_val_pred, average='weighted')

#     # Print performance metrics
#     print("Validation Metrics:")
#     print(f"\tAccuracy: {val_accuracy:.4f}")
#     print(f"\tPrecision: {val_precision:.4f}")
#     print(f"\tRecall: {val_recall:.4f}")
#     print(f"\tF1 Score: {val_f1:.4f}")
#     print("*"*100)
```

The above grid search did not converge for the 'linear' kernel therefore, I ran and tuned each hyper parameter seperately in the following cells.

In [30]:
```
# Tuning 'linear' svm for C hyper parameter
from sklearn.svm import SVC
svm_c = [3, 4, 5, 6, 7, 8]
for c in svm_c:
    svm_classifier = SVC(random_state=42, C = c, kernel= 'linear', gamma = 1, pr
    svm_classifier.fit(X_train, y_train)

    # Validation set performance
```

```
    y_val_pred = svm_classifier.predict(X_validation)
    val_accuracy = accuracy_score(y_validation, y_val_pred)
    val_precision = precision_score(y_validation, y_val_pred, average='weighted'
    val_recall = recall_score(y_validation, y_val_pred, average='weighted')
    val_f1 = f1_score(y_validation, y_val_pred, average='weighted')

    # Print performance metrics
    print(f"For c = ", c)
    print("Validation Metrics:")
    print(f"\tAccuracy: {val_accuracy:.4f}")
    print(f"\tPrecision: {val_precision:.4f}")
    print(f"\tRecall: {val_recall:.4f}")
    print(f"\tF1 Score: {val_f1:.4f}")
    print("*"*100)
```

```
For c =  3
Validation Metrics:
        Accuracy: 0.7472
        Precision: 0.7428
        Recall: 0.7472
        F1 Score: 0.7438
*********************************************************************************
*******************
For c =  4
Validation Metrics:
        Accuracy: 0.7472
        Precision: 0.7428
        Recall: 0.7472
        F1 Score: 0.7438
*********************************************************************************
*******************
For c =  5
Validation Metrics:
        Accuracy: 0.7472
        Precision: 0.7428
        Recall: 0.7472
        F1 Score: 0.7438
*********************************************************************************
*******************
For c =  6
Validation Metrics:
        Accuracy: 0.7472
        Precision: 0.7428
        Recall: 0.7472
        F1 Score: 0.7438
*********************************************************************************
*******************
For c =  7
Validation Metrics:
        Accuracy: 0.7472
        Precision: 0.7428
        Recall: 0.7472
        F1 Score: 0.7438
*********************************************************************************
*******************
For c =  8
Validation Metrics:
        Accuracy: 0.7472
        Precision: 0.7428
        Recall: 0.7472
        F1 Score: 0.7438
*********************************************************************************
*******************
```

From the above code the best accuracy (0.7474) for the Validation Data is obtained when C = 4. Tuning Gamma below -

In [31]:

```
# Tuning 'linear' svm for gamma hyper parameter
from sklearn.svm import SVC
svm_g = [0.001, 0.01, 0.1, 1, 2, 3, 4]
for g in svm_g:
    svm_classifier = SVC(random_state=42, C = 4, kernel= 'linear', gamma = g, pr
    svm_classifier.fit(X_train, y_train)
```

```
    # Validation set performance
    y_val_pred = svm_classifier.predict(X_validation)
    val_accuracy = accuracy_score(y_validation, y_val_pred)
    val_precision = precision_score(y_validation, y_val_pred, average='weighted'
    val_recall = recall_score(y_validation, y_val_pred, average='weighted')
    val_f1 = f1_score(y_validation, y_val_pred, average='weighted')

    # Print performance metrics
    print(f"For Gamma = ", g)
    print("Validation Metrics:")
    print(f"\tAccuracy: {val_accuracy:.4f}")
    print(f"\tPrecision: {val_precision:.4f}")
    print(f"\tRecall: {val_recall:.4f}")
    print(f"\tF1 Score: {val_f1:.4f}")
    print("*"*100)
```

```
For Gamma =  0.001
Validation Metrics:
        Accuracy: 0.7472
        Precision: 0.7428
        Recall: 0.7472
        F1 Score: 0.7438
*********************************************************************************
*******************
For Gamma =  0.01
Validation Metrics:
        Accuracy: 0.7472
        Precision: 0.7428
        Recall: 0.7472
        F1 Score: 0.7438
*********************************************************************************
*******************
For Gamma =  0.1
Validation Metrics:
        Accuracy: 0.7472
        Precision: 0.7428
        Recall: 0.7472
        F1 Score: 0.7438
*********************************************************************************
*******************
For Gamma =  1
Validation Metrics:
        Accuracy: 0.7472
        Precision: 0.7428
        Recall: 0.7472
        F1 Score: 0.7438
*********************************************************************************
*******************
For Gamma =  2
Validation Metrics:
        Accuracy: 0.7472
        Precision: 0.7428
        Recall: 0.7472
        F1 Score: 0.7438
*********************************************************************************
*******************
For Gamma =  3
Validation Metrics:
        Accuracy: 0.7472
        Precision: 0.7428
        Recall: 0.7472
        F1 Score: 0.7438
*********************************************************************************
*******************
For Gamma =  4
Validation Metrics:
        Accuracy: 0.7472
        Precision: 0.7428
        Recall: 0.7472
        F1 Score: 0.7438
*********************************************************************************
*******************
```

- **From the above code the we can see that Accuracy for the Validation data does not change so gamma = 0.01** is used.

- **Finalizing & Selecting the best 'linear' model below,**
    - **Out of the 3 kernels - 'rbf', 'sigmoid' & 'linear', the 'rbf' model is the best as it produces the highest Validation Data Accuracy.**

In [32]:
```
# Finalizing 'linear' svm for gamma hyper parameter
from sklearn.svm import SVC

final_svm_classifier = SVC(random_state=42, probability=True, C = 5, kernel = 'r
final_svm_classifier.fit(X_train, y_train.values.ravel())

# Train Data Performance
y_train_pred = final_svm_classifier.predict(X_train)
train_accuracy = accuracy_score(y_train, y_train_pred)
train_precision = precision_score(y_train, y_train_pred, average='weighted')
train_recall = recall_score(y_train, y_train_pred, average='weighted')
train_f1 = f1_score(y_train, y_train_pred, average='weighted')

# Print Training Performance metrics
print("Training Metrics:")
print(f"\tAccuracy: {train_accuracy:.4f}")
print(f"\tPrecision: {train_precision:.4f}")
print(f"\tRecall: {train_recall:.4f}")
print(f"\tF1 Score: {train_f1:.4f}")

# Validation set performance
y_val_pred = final_svm_classifier.predict(X_validation)
val_accuracy = accuracy_score(y_validation, y_val_pred)
val_precision = precision_score(y_validation, y_val_pred, average='weighted')
val_recall = recall_score(y_validation, y_val_pred, average='weighted')
val_f1 = f1_score(y_validation, y_val_pred, average='weighted')

# Print performance metrics
print("\nValidation Metrics:")
print(f"\tAccuracy: {val_accuracy:.4f}")
print(f"\tPrecision: {val_precision:.4f}")
print(f"\tRecall: {val_recall:.4f}")
print(f"\tF1 Score: {val_f1:.4f}")

# Test set performance
y_test_pred = final_svm_classifier.predict(X_test)
test_accuracy = accuracy_score(y_test, y_test_pred)
test_precision = precision_score(y_test, y_test_pred, average='weighted')
test_recall = recall_score(y_test, y_test_pred, average='weighted')
test_f1 = f1_score(y_test, y_test_pred, average='weighted')

# Print performance metrics
print("\nTest Metrics:")
print(f"\tAccuracy: {test_accuracy:.4f}")
print(f"\tPrecision: {test_precision:.4f}")
print(f"\tRecall: {test_recall:.4f}")
print(f"\tF1 Score: {test_f1:.4f}")
```

```
Training Metrics:
        Accuracy: 0.7247
        Precision: 0.7282
        Recall: 0.7247
        F1 Score: 0.7018

Validation Metrics:
        Accuracy: 0.7528
        Precision: 0.7590
        Recall: 0.7528
        F1 Score: 0.7325

Test Metrics:
        Accuracy: 0.6872
        Precision: 0.7076
        Recall: 0.6872
        F1 Score: 0.6594
```

From the above simulations it can be seen that the best model for SVM, based on Validation Data is the one with 'rbf' kernel, which provide the higgest accuracy for validation data with C = 5, Degree = 2 & Gamma = 0.0001

Random Forrest Classifier

In [33]:
```
from sklearn.ensemble import RandomForestClassifier

# Define hyperparameter grid
param_grid = {
    'n_estimators': [120, 130, 140, 150],  # Number of trees
    'max_depth': [7, 8, 9, 10, 11, 12],  # Maximum depth of trees
    'min_samples_split': [1, 2, 3, 4],  # Minimum samples required to split
    'min_samples_leaf': [2, 4, 5]  # Minimum samples required at leaf nodes
}

# Create the Random Forest classifier
random_forest = RandomForestClassifier(random_state=42)

# Running a for loop to determine the best cv score and checkig the Validation A
for rfc in range(2,9):
    # Grid search to find the best hyperparameters
    grid_search_rf = GridSearchCV(random_forest, param_grid, cv = rfc, scoring =
    grid_search_rf.fit(X_train, y_train.values.ravel())

    # Get the best hyperparameters
    best_params_rf = grid_search_rf.best_params_
    print(f"For cv = ", rfc)
    print("Best Parameters are: ", best_params_rf)
    print("The accuracy score for the above parameters: ", grid_search_rf.best_s

    # Train the model with the best hyperparameters
    best_random_forest = RandomForestClassifier(random_state=42, **best_params_r
    best_random_forest.fit(X_train, y_train.values.ravel())

    # Validation set performance
    y_val_pred = best_random_forest.predict(X_validation)
```

```
    val_accuracy = accuracy_score(y_validation, y_val_pred)
    val_precision = precision_score(y_validation, y_val_pred, average='weighted'
    val_recall = recall_score(y_validation, y_val_pred, average='weighted')
    val_f1 = f1_score(y_validation, y_val_pred, average='weighted')

    # Print performance metrics
    print("Validation Metrics:")
    print(f"\tAccuracy: {val_accuracy:.4f}")
    print(f"\tPrecision: {val_precision:.4f}")
    print(f"\tRecall: {val_recall:.4f}")
    print(f"\tF1 Score: {val_f1:.4f}")
    print("*"*100)
```

```
For cv =  2
Best Parameters are:  {'max_depth': 11, 'min_samples_leaf': 2, 'min_samples_spli
t': 2, 'n_estimators': 120}
The accuracy score for the above parameters:  0.8314606741573034
Validation Metrics:
        Accuracy: 0.8146
        Precision: 0.8139
        Recall: 0.8146
        F1 Score: 0.8093
*********************************************************************************
*******************
For cv =  3
Best Parameters are:  {'max_depth': 9, 'min_samples_leaf': 5, 'min_samples_spli
t': 2, 'n_estimators': 130}
The accuracy score for the above parameters:  0.8426966292134832
Validation Metrics:
        Accuracy: 0.8090
        Precision: 0.8084
        Recall: 0.8090
        F1 Score: 0.8030
*********************************************************************************
*******************
For cv =  4
Best Parameters are:  {'max_depth': 7, 'min_samples_leaf': 2, 'min_samples_spli
t': 2, 'n_estimators': 140}
The accuracy score for the above parameters:  0.8352036808439008
Validation Metrics:
        Accuracy: 0.8146
        Precision: 0.8171
        Recall: 0.8146
        F1 Score: 0.8071
*********************************************************************************
*******************
For cv =  5
Best Parameters are:  {'max_depth': 8, 'min_samples_leaf': 4, 'min_samples_spli
t': 2, 'n_estimators': 150}
The accuracy score for the above parameters:  0.8483688943748898
Validation Metrics:
        Accuracy: 0.8202
        Precision: 0.8206
        Recall: 0.8202
        F1 Score: 0.8146
*********************************************************************************
*******************
For cv =  6
Best Parameters are:  {'max_depth': 7, 'min_samples_leaf': 2, 'min_samples_spli
t': 2, 'n_estimators': 140}
The accuracy score for the above parameters:  0.8464419475655433
Validation Metrics:
        Accuracy: 0.8146
        Precision: 0.8171
        Recall: 0.8146
        F1 Score: 0.8071
*********************************************************************************
*******************
For cv =  7
Best Parameters are:  {'max_depth': 7, 'min_samples_leaf': 2, 'min_samples_spli
t': 2, 'n_estimators': 120}
The accuracy score for the above parameters:  0.8462552485108876
Validation Metrics:
```

```
        Accuracy: 0.8090
        Precision: 0.8118
        Recall: 0.8090
        F1 Score: 0.8007
********************************************************************************
*******************
For cv =  8
Best Parameters are:  {'max_depth': 9, 'min_samples_leaf': 2, 'min_samples_spli
t': 2, 'n_estimators': 120}
The accuracy score for the above parameters:  0.8408808231569426
Validation Metrics:
        Accuracy: 0.8090
        Precision: 0.8099
        Recall: 0.8090
        F1 Score: 0.8019
********************************************************************************
*******************
```

- ## From the above model with a cv = 5 & with a high Validation Accuracy of 0.8202 is selected. This model has the highest training accuracy or 0.8483688943748898.

In [34]:

```python
from sklearn.ensemble import RandomForestClassifier

# Define hyperparameter grid
param_grid = {
    'n_estimators': [100, 110, 120, 130, 140, 150],  # Number of trees
    'max_depth': [10, 11, 12, 13, 14, 15],  # Maximum depth of trees
    'min_samples_split': [1, 2, 3, 4],  # Minimum samples required to split
    'min_samples_leaf': [2, 4, 5, 6, 7]  # Minimum samples required at leaf node
}

# Create the Random Forest classifier
random_forest = RandomForestClassifier(random_state=42)

# Grid search to find the best hyperparameters
grid_search_rf = GridSearchCV(random_forest, param_grid, cv = 5, scoring = 'accu
grid_search_rf.fit(X_train, y_train.values.ravel())

# Get the best hyperparameters
best_params_rf = grid_search_rf.best_params_
print("Best Parameters are: ", best_params_rf)
print("The accuracy score for the above parameters: ", grid_search_rf.best_score

# Train the model with the best hyperparameters
best_random_forest = RandomForestClassifier(random_state=42, **best_params_rf)
best_random_forest.fit(X_train, y_train.values.ravel())

# Validation set performance
y_val_pred = best_random_forest.predict(X_validation)
val_accuracy = accuracy_score(y_validation, y_val_pred)
val_precision = precision_score(y_validation, y_val_pred, average='weighted')
val_recall = recall_score(y_validation, y_val_pred, average='weighted')
val_f1 = f1_score(y_validation, y_val_pred, average='weighted')

# Print performance metrics
```

```
print("Validation Metrics:")
print(f"\tAccuracy: {val_accuracy:.4f}")
print(f"\tPrecision: {val_precision:.4f}")
print(f"\tRecall: {val_recall:.4f}")
print(f"\tF1 Score: {val_f1:.4f}")
```

```
Best Parameters are:  {'max_depth': 10, 'min_samples_leaf': 4, 'min_samples_spli
t': 2, 'n_estimators': 120}
The accuracy score for the above parameters:  0.8483688943748898
Validation Metrics:
	Accuracy: 0.8090
	Precision: 0.8084
	Recall: 0.8090
	F1 Score: 0.8030
```

- **From the above model we can observer that when the cv = 5, the best parameters are -**
    - **{'max_depth': 12, 'min_samples_leaf': 5, 'min_samples_split': 2, 'n_estimators': 120}**
- **Using these hyper parameters the model is fine tuned below -**

In [35]:

```
from sklearn.ensemble import RandomForestClassifier

# Finalizing the Random Forest classifier
final_random_forest = RandomForestClassifier(random_state=42, max_depth = 10, mi
                                             min_samples_split = 2, n_estimators
final_random_forest.fit(X_train, y_train.values.ravel())

# Train Data Performance
y_train_pred = final_random_forest.predict(X_train)
train_accuracy = accuracy_score(y_train, y_train_pred)
train_precision = precision_score(y_train, y_train_pred, average='weighted')
train_recall = recall_score(y_train, y_train_pred, average='weighted')
train_f1 = f1_score(y_train, y_train_pred, average='weighted')

# Print Training Performance metrics
print("Training Metrics:")
print(f"\tAccuracy: {train_accuracy:.4f}")
print(f"\tPrecision: {train_precision:.4f}")
print(f"\tRecall: {train_recall:.4f}")
print(f"\tF1 Score: {train_f1:.4f}")

# Validation set performance
y_val_pred = final_random_forest.predict(X_validation)
val_accuracy = accuracy_score(y_validation, y_val_pred)
val_precision = precision_score(y_validation, y_val_pred, average='weighted')
val_recall = recall_score(y_validation, y_val_pred, average='weighted')
val_f1 = f1_score(y_validation, y_val_pred, average='weighted')

# Test set performance
y_test_pred = final_random_forest.predict(X_test)
test_accuracy = accuracy_score(y_test, y_test_pred)
test_precision = precision_score(y_test, y_test_pred, average='weighted')
test_recall = recall_score(y_test, y_test_pred, average='weighted')
test_f1 = f1_score(y_test, y_test_pred, average='weighted')
```

```
# Print performance metrics
print("\nValidation Metrics:")
print(f"\tAccuracy: {val_accuracy:.4f}")
print(f"\tPrecision: {val_precision:.4f}")
print(f"\tRecall: {val_recall:.4f}")
print(f"\tF1 Score: {val_f1:.4f}")

# Print performance metrics
print("\nTest Metrics:")
print(f"\tAccuracy: {test_accuracy:.4f}")
print(f"\tPrecision: {test_precision:.4f}")
print(f"\tRecall: {test_recall:.4f}")
print(f"\tF1 Score: {test_f1:.4f}")
```

```
Training Metrics:
        Accuracy: 0.9101
        Precision: 0.9138
        Recall: 0.9101
        F1 Score: 0.9083

Validation Metrics:
        Accuracy: 0.8202
        Precision: 0.8206
        Recall: 0.8202
        F1 Score: 0.8146

Test Metrics:
        Accuracy: 0.8324
        Precision: 0.8393
        Recall: 0.8324
        F1 Score: 0.8286
```

Compared to the Grid Search -

1. There is no change in the Validation Accuracy after changing the min_samples_leaf, or min_samples_split.
2. The Model performs adequately when max_depth = 10, & n_estimators = 150.
3. Therefore, the following hyperparameters are the optimum for SVM using 'sigmoid' kernel -
    - {'max_depth': 10, 'min_samples_leaf': 2, 'min_samples_split': 2, 'n_estimators': 150}

Question 5
Combine your classifiers into an ensemble and try to outperform each individual classifier on the validation set (try to get above 80% accuracy). Once you have found a good one, try it on the test set. Describe and discuss your findings.

In [36]:
```
from sklearn.ensemble import VotingClassifier

# Create the ensemble of classifiers
ensemble_classifier_hard = VotingClassifier(
    estimators=[
        ('logistic_regression', final_logistic_regression),
        ('svm_classifier', final_svm_classifier),
        ('random_forest', final_random_forest)
    ],
    voting='hard'  # Use majority voting
)

# Train the ensemble on the training data
ensemble_classifier_hard.fit(X_train, y_train.values.ravel())

# Evaluate the ensemble on the validation set
y_val_ensemble_pred = ensemble_classifier_hard.predict(X_validation)
val_ensemble_accuracy = accuracy_score(y_validation, y_val_ensemble_pred)
val_ensemble_precision = precision_score(y_validation, y_val_ensemble_pred, aver
val_ensemble_recall = recall_score(y_validation, y_val_ensemble_pred, average='w
val_ensemble_f1 = f1_score(y_validation, y_val_ensemble_pred, average='weighted'

# Train Data Performance
y_train_pred = ensemble_classifier_hard.predict(X_train)
train_accuracy = accuracy_score(y_train, y_train_pred)
train_precision = precision_score(y_train, y_train_pred, average='weighted')
train_recall = recall_score(y_train, y_train_pred, average='weighted')
train_f1 = f1_score(y_train, y_train_pred, average='weighted')

# Print Training Performance metrics
print("Training Metrics:")
print(f"\tAccuracy: {train_accuracy:.4f}")
print(f"\tPrecision: {train_precision:.4f}")
print(f"\tRecall: {train_recall:.4f}")
print(f"\tF1 Score: {train_f1:.4f}")

# Print Validation Data metrics
print(f"\nValidation Data Metrics: ")
print(f"\tAccuracy: {val_ensemble_accuracy:.4f}")
print(f"\tPrecision: {val_ensemble_precision:.4f}")
print(f"\tRecall: {val_ensemble_recall:.4f}")
print(f"\tF1 Score: {val_ensemble_f1:.4f}")

# Evaluate the ensemble on the test set
y_test_ensemble_pred = ensemble_classifier_hard.predict(X_test)
test_ensemble_accuracy = accuracy_score(y_test, y_test_ensemble_pred)
test_ensemble_precision = precision_score(y_test, y_test_ensemble_pred, average=
test_ensemble_recall = recall_score(y_test, y_test_ensemble_pred, average='weigh
test_ensemble_f1 = f1_score(y_test, y_test_ensemble_pred, average='weighted')

# Print Test Data metrics
print(f"\nTest Accuracy:")
print(f"\tAccuracy: {test_ensemble_accuracy:.4f}")
print(f"\tPrecision: {test_ensemble_precision:.4f}")
print(f"\tRecall: {test_ensemble_recall:.4f}")
print(f"\tF1 Score: {test_ensemble_f1:.4f}")
```

```
Training Metrics:
	Accuracy: 0.8745
	Precision: 0.8779
	Recall: 0.8745
	F1 Score: 0.8715

Validation Data Metrics:
	Accuracy: 0.8202
	Precision: 0.8194
	Recall: 0.8202
	F1 Score: 0.8156

Test Accuracy:
	Accuracy: 0.8212
	Precision: 0.8299
	Recall: 0.8212
	F1 Score: 0.8164
```

In [37]:

```
# Create the ensemble of classifiers
ensemble_classifier_soft = VotingClassifier(
    estimators=[
        ('logistic_regression', final_logistic_regression),
        ('svm_classifier', final_svm_classifier),
        ('random_forest', final_random_forest)
    ],
    voting='soft',  # Use soft voting
    flatten_transform=True,  # Enable probability estimation
)

# Train the ensemble on the training data
ensemble_classifier_soft.fit(X_train, y_train.values.ravel())

# Train Data Performance
y_train_pred = ensemble_classifier_soft.predict(X_train)
train_accuracy = accuracy_score(y_train, y_train_pred)
train_precision = precision_score(y_train, y_train_pred, average='weighted')
train_recall = recall_score(y_train, y_train_pred, average='weighted')
train_f1 = f1_score(y_train, y_train_pred, average='weighted')

# Print Training Performance metrics
print("Training Metrics:")
print(f"\tAccuracy: {train_accuracy:.4f}")
print(f"\tPrecision: {train_precision:.4f}")
print(f"\tRecall: {train_recall:.4f}")
print(f"\tF1 Score: {train_f1:.4f}")

# Evaluate the ensemble on the validation set
y_val_ensemble_pred = ensemble_classifier_soft.predict(X_validation)
val_ensemble_accuracy = accuracy_score(y_validation, y_val_ensemble_pred)
val_ensemble_precision = precision_score(y_validation, y_val_ensemble_pred, aver
val_ensemble_recall = recall_score(y_validation, y_val_ensemble_pred, average='w
val_ensemble_f1 = f1_score(y_validation, y_val_ensemble_pred, average='weighted'

# Print Validation Data metrics
print(f"\nValidation Data Metrics: ")
print(f"\tAccuracy: {val_ensemble_accuracy:.4f}")
print(f"\tPrecision: {val_ensemble_precision:.4f}")
print(f"\tRecall: {val_ensemble_recall:.4f}")
print(f"\tF1 Score: {val_ensemble_f1:.4f}")
```

```
# Evaluate the ensemble on the test set
y_test_ensemble_pred = ensemble_classifier_soft.predict(X_test)
test_ensemble_accuracy = accuracy_score(y_test, y_test_ensemble_pred)
test_ensemble_precision = precision_score(y_test, y_test_ensemble_pred, average=
test_ensemble_recall = recall_score(y_test, y_test_ensemble_pred, average='weigh
test_ensemble_f1 = f1_score(y_test, y_test_ensemble_pred, average='weighted')

# Print Test Data metrics
print(f"\nTest Accuracy:")
print(f"\tAccuracy: {test_ensemble_accuracy:.4f}")
print(f"\tPrecision: {test_ensemble_precision:.4f}")
print(f"\tRecall: {test_ensemble_recall:.4f}")
print(f"\tF1 Score: {test_ensemble_f1:.4f}")
```

```
Training Metrics:
        Accuracy: 0.8764
        Precision: 0.8796
        Recall: 0.8764
        F1 Score: 0.8735

Validation Data Metrics:
        Accuracy: 0.8090
        Precision: 0.8068
        Recall: 0.8090
        F1 Score: 0.8051

Test Accuracy:
        Accuracy: 0.8045
        Precision: 0.8160
        Recall: 0.8045
        F1 Score: 0.7978
```

Answer 5

As seen from the above 2 ensemble models -

1. Hard Ensemble
    - **The Hard Ensemble is able to predict the Validation set with a 82%+ overall validation accuracy.**
    - **This Validation Data Accuracy obtained is greater than individual Multinomial Logistic Regression & SVM classifiers & Very close to the Random Forest Classifier.**
    - **The Hard Ensemble is slightly more accurate for the Test Data, compare to the Validation Data. This could be because there might be fewer training instances for the model to train, due to which the classifiers might be underfitting the data.**

2. Soft Ensemble
    - **The Soft Ensemble is able to predict the Validation set with a almost 81% accuracy for the Validation and the Test Data as it takes an average of all the 3 classifiers.**
    - **The Soft Accuracy is being slightly reduced due to the low Accuracy of Multinomial Logistic Regression & SVM Classifier.**
    - **Therefore, we can conclude that in this case the Soft Voting Ensemble is a better choice compared to the Hard Voting Ensemble, as even though the Test & Validation data accuracy is very close to each other for both the ensemble models, Soft Ensemble might be able to produce better results as it**

combines the probabilities predicted by all the classifiers.

3. **For Training Data set Accuracy both the ensemble models produces approximilately similar results.**

4. **There is no significance difference between accuracies provided by the Hard or Soft ensemble, but the Test Accuracy is a bit higher than the Validation Accuracy. Due to which it could be said that the model is slightly underfitting the data, which could be fixed with more training data.**