Problem Statement:

The Titanic Problem is based on the sinking of the 'Unsinkable' ship Titanic in early 1912. It gives you information about multiple people like their ages, sexes, sibling counts, embarkment points, and whether or not they survived the disaster. Based on these features, you have to predict if an arbitrary passenger on Titanic would survive the sinking or not.

Importing required libraries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_sco
from scipy.stats import zscore
import scikitplot as skplt
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import confusion_matrix, classification_report, accuracy_sco
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

Reading data

In [2]:
```
df = pd.read_csv(r"C:\Users\Kushal Arya\Desktop\Data Analysis With Python\ML File
df.head()
```

Out[2]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabi
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	Na
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C8
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	Na
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C12
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	Na

Check no of row and column

In [3]:
```
print('No of Rows and Columns ----->', df.shape )
```

```
No of Rows and Columns -----> (891, 12)
```

Checking for Null values

In [4]:
```
print('---------------------\n')
print(df.isnull().sum())
print('\n---------------------')
```

```
---------------------

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

---------------------
```

Information about dataset

In [5]:
```
print('---------------------------------------------------\n')
print(df.info())
print('\n---------------------------------------------------')
```

```
---------------------------------------------------

<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
None

---------------------------------------------------
```

There is Sex, Name, Ticket, Cabin and Embarked feature which is object type we have convert into int.

Droping Unwanted Column

In [6]:
```
col = ['PassengerId', 'Name', 'Ticket', 'Cabin']
```

In [7]:
```
df = df.drop(columns = col, axis = 1)
df.head()
```

Out[7]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.2500	S
1	1	1	female	38.0	1	0	71.2833	C
2	1	3	female	26.0	0	0	7.9250	S
3	1	1	female	35.0	1	0	53.1000	S
4	0	3	male	35.0	0	0	8.0500	S

We drop Cabin because it has more than 50% data is missing or other words more than 50% NaN present.

Handling missing data

In [8]:
```
df['Age'] = df['Age'].fillna(df['Age'].median())
df['Embarked'] = df['Embarked'].fillna(df['Embarked'].mode()[0])
```

In [9]:
```
# check nan remove or not
df.isna().sum()
```

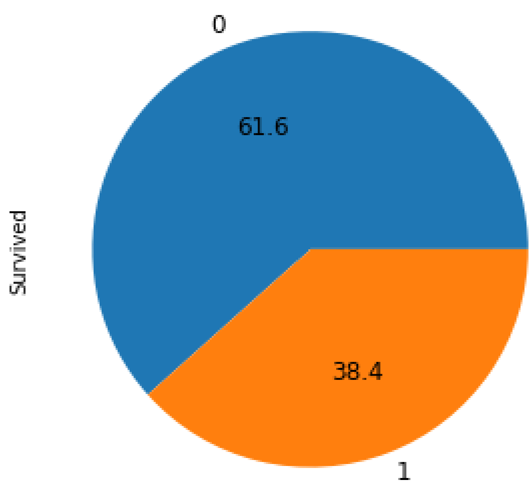
Out[9]:
```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
```

NaN removed from our dataset.

Relation feature and feature

In [10]:
```
s = df['Survived'].value_counts()
s
```
Out[10]:
```
0    549
1    342
Name: Survived, dtype: int64
```

In [11]:
```
s.plot.pie( fontsize = 12, autopct = '%.1f',figsize = (10,5))
plt.show()
```



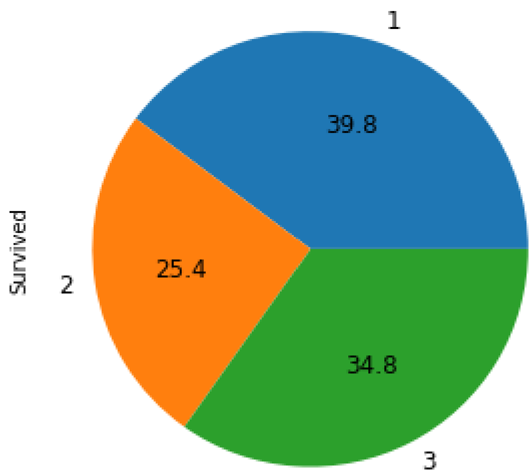
Observation : 61.6% people died and 38.4% people survived.

In [12]:
```
df['Pclass'].value_counts()
```
Out[12]:
```
3    491
1    216
2    184
Name: Pclass, dtype: int64
```

In [13]:
```
print('-------------------------------------')
print(df.groupby('Pclass')['Survived'].sum())
print('-------------------------------------')
```
```
-------------------------------------
Pclass
1    136
2     87
3    119
Name: Survived, dtype: int64
-------------------------------------
```

In [14]:
```
p = df.groupby('Pclass')['Survived'].sum()
```

In [15]:
```
p.plot.pie( fontsize = 12, autopct = '%.1f',figsize = (10,5))
plt.show()
```



Observation : 1st class passanger Survived more compare to other class and 2nd class passanger Survived least.

In [16]:
```
df['Fare'].value_counts()
```

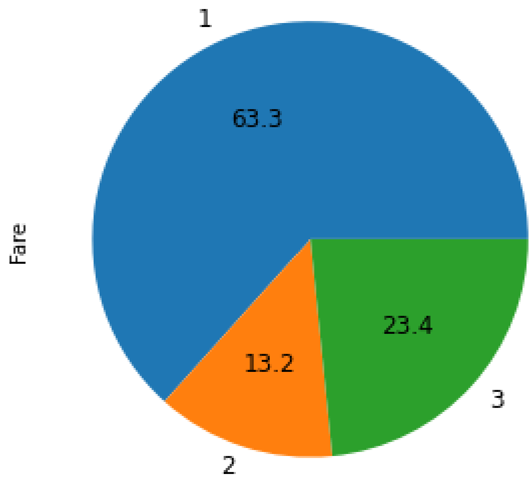
Out[16]:
```
8.0500     43
13.0000    42
7.8958     38
7.7500     34
26.0000    31
           ..
50.4958     1
13.8583     1
8.4583      1
7.7250      1
7.5208      1
Name: Fare, Length: 248, dtype: int64
```

In [17]:
```
print('-------------------------------------')
print(df.groupby('Pclass')['Fare'].sum())
print('-------------------------------------')
```

```
-------------------------------------
Pclass
1    18177.4125
2     3801.8417
3     6714.6951
Name: Fare, dtype: float64
-------------------------------------
```

In [18]:
```
f = df.groupby('Pclass')['Fare'].sum()
```

In [19]:
```
f.plot.pie( fontsize = 12, autopct = '%.1f',figsize = (10,5))
plt.show()
```



Observation : 1st class passanger spent more on tickets.

In [20]:
```
df['Age'].value_counts()
```

Out[20]:
```
28.00    202
24.00     30
22.00     27
18.00     26
19.00     25
        ...
55.50      1
74.00      1
0.92       1
70.50      1
12.00      1
Name: Age, Length: 88, dtype: int64
```

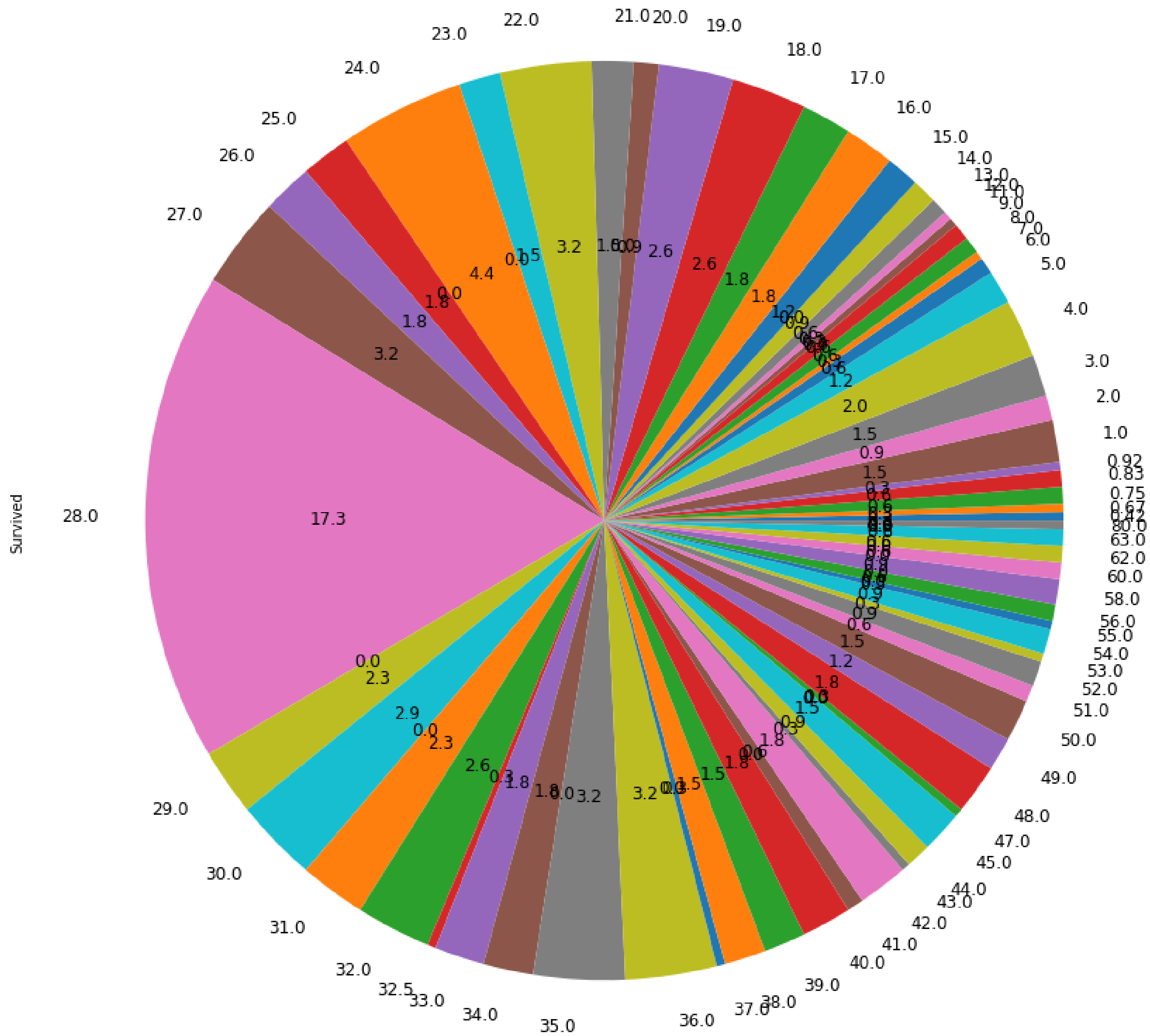
In [21]:
```python
print('-------------------------------------')
print(df.groupby('Age')['Survived'].sum())
print('-------------------------------------')
```

```
-------------------------------------
Age
0.42     1
0.67     1
0.75     2
0.83     2
0.92     1
        ..
70.00    0
70.50    0
71.00    0
74.00    0
80.00    1
Name: Survived, Length: 88, dtype: int64
-------------------------------------
```

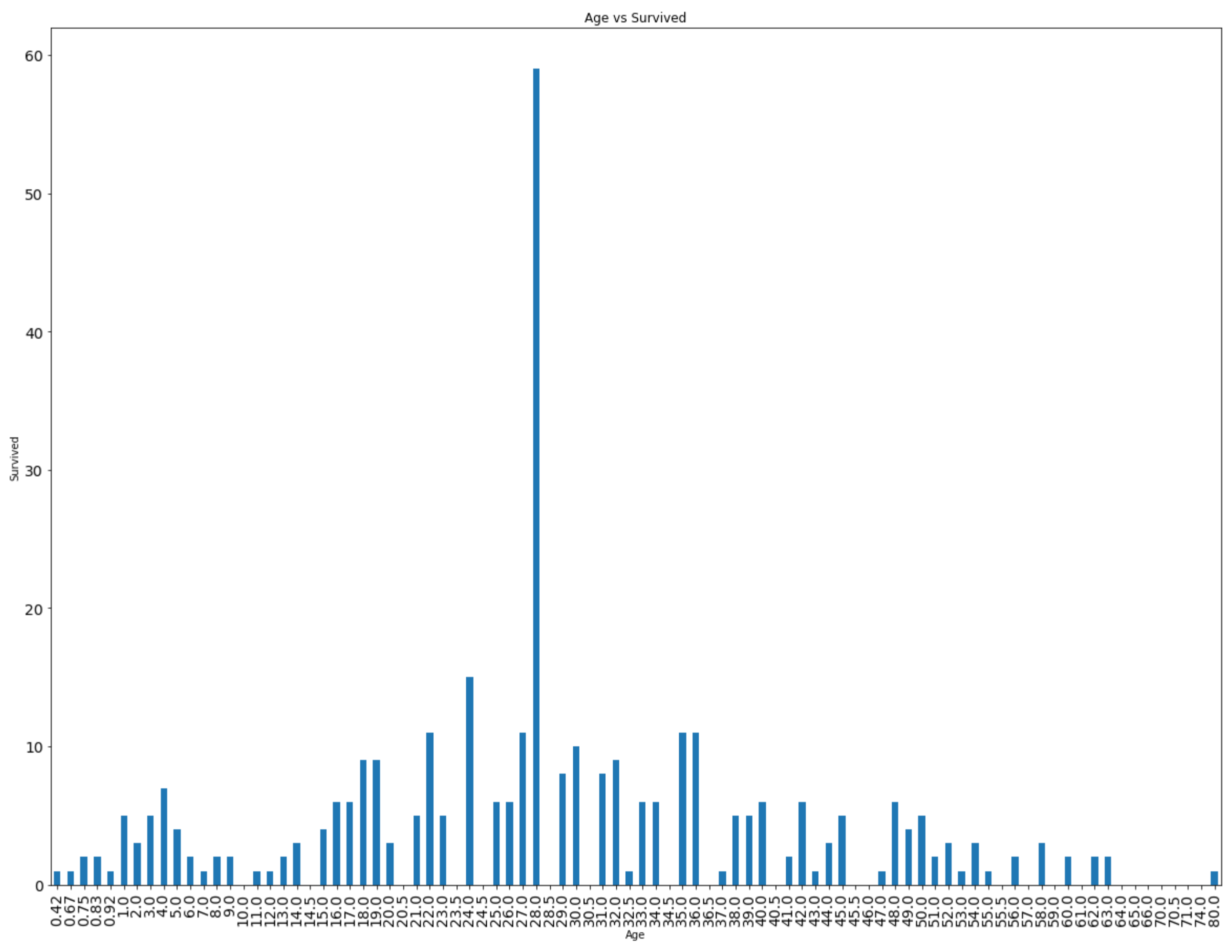
In [22]:
```python
a = df.groupby('Age')['Survived'].sum()
```

In [23]:

```python
a.plot.pie( fontsize = 12, autopct = '%.1f',figsize = (20,15))
plt.show()
```



In [24]:
```
a.plot.bar(figsize = (20,15), fontsize = 14)
plt.xlabel('Age')
plt.ylabel('Survived')
plt.title('Age vs Survived')
plt.show()
```



Observation :Above both plot shows age group of 24 and 36 is more Survived.

Checking for Imbalance Label

In [25]:
```
print('-----------------------------------')
print('No of Survived present in Titanic :')
print('-----------------------------------')
print(df['Survived'].value_counts())
print('-----------------------------------')
```

```
-----------------------------------
No of Survived present in Titanic :
-----------------------------------
0    549
1    342
Name: Survived, dtype: int64
-----------------------------------
```

Observation : Class is balanced.

Label Encoder

In [26]:
```
lab_enc = LabelEncoder()
df['Sex'] = lab_enc.fit_transform(df['Sex'])
```

In [27]:
```
lab_enc = LabelEncoder()
df['Embarked'] = lab_enc.fit_transform(df['Embarked'])
```

In [28]:
```
df.head()
```

Out[28]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	1	22.0	1	0	7.2500	2
1	1	1	0	38.0	1	0	71.2833	0
2	1	3	0	26.0	0	0	7.9250	2
3	1	1	0	35.0	1	0	53.1000	2
4	0	3	1	35.0	0	0	8.0500	2

In [29]:
```
df.info()
```

```
<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    int32  
 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    int32  
dtypes: float64(2), int32(2), int64(4)
memory usage: 48.9 KB
```

Converting categorical into numrical value is done.

Statistic of Dataset

In [71]:
```
# We use describe command to extracte statistical infomation about dataset.
df.describe()
```

Out[71]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Emba
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.00
mean	0.383838	2.308642	0.647587	29.361582	0.523008	0.381594	32.204208	1.53
std	0.486592	0.836071	0.477990	13.019697	1.102743	0.806057	49.693429	0.79
min	0.000000	1.000000	0.000000	0.420000	0.000000	0.000000	0.000000	0.00
25%	0.000000	2.000000	0.000000	22.000000	0.000000	0.000000	7.910400	1.00
50%	0.000000	3.000000	1.000000	28.000000	0.000000	0.000000	14.454200	2.00
75%	1.000000	3.000000	1.000000	35.000000	1.000000	0.000000	31.000000	2.00
max	1.000000	3.000000	1.000000	80.000000	8.000000	6.000000	512.329200	2.00

Plot how data is distributed

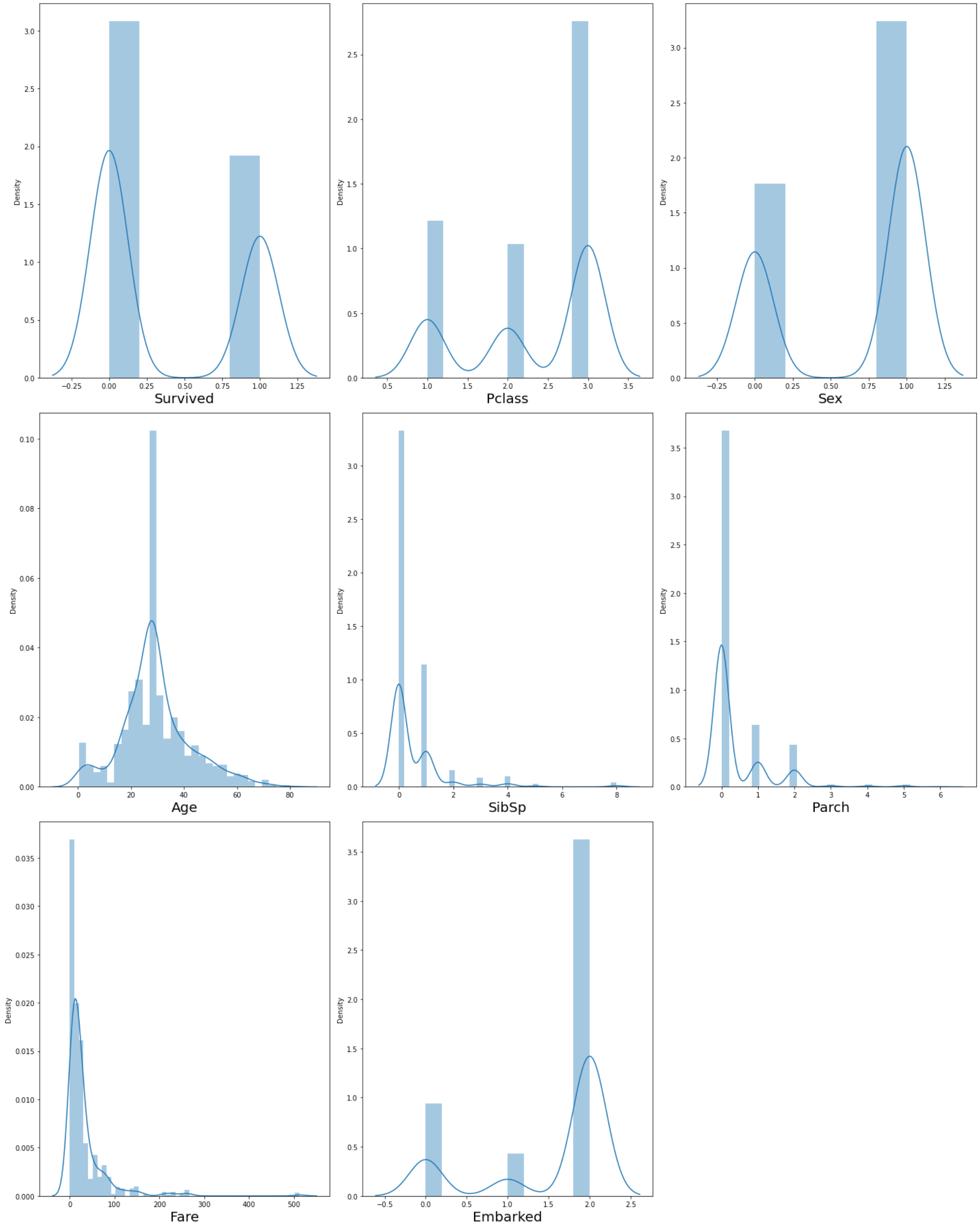
In [30]:

```
print('---------------------')
print('Distribution Plot :- ')
print('---------------------')

plt.figure(figsize = (20,25))
plotnumber = 1

for column in df:
    if plotnumber <=9:
        ax = plt.subplot(3,3, plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column, fontsize = 20)
    plotnumber +=1
plt.tight_layout()
```

```
---------------------
Distribution Plot :-
---------------------
```



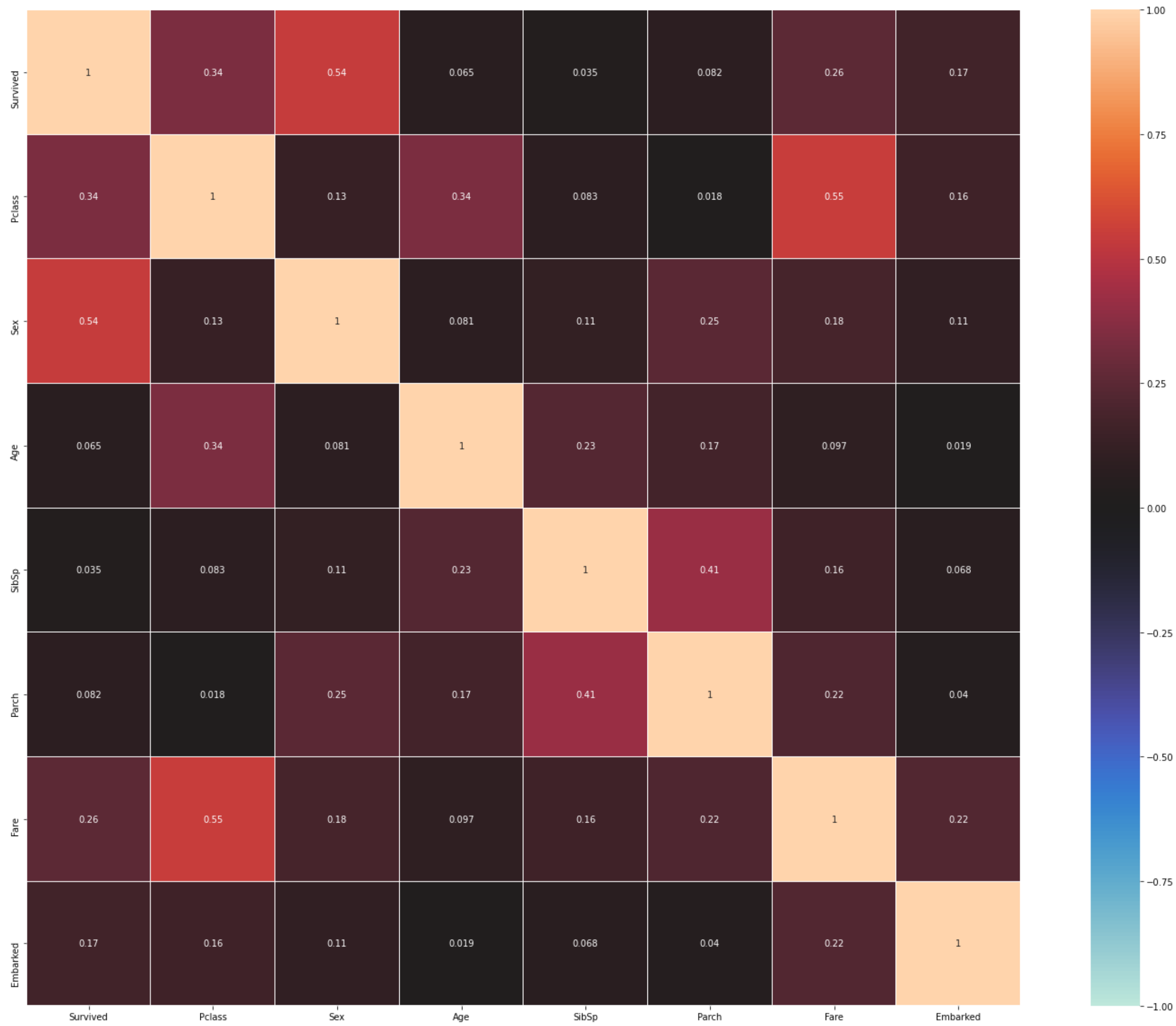
Observation :Above both plot shows their is no outliers.

Corelation of Feature vs Label using Heat map

In [31]:
```python
print('-----------')
print('Heat Map :-')
print('-----------')
df_corr = df.corr().abs()

plt.figure(figsize = (22,16))
sns.heatmap(df_corr, vmin = -1, annot = True, square = True, center = 0, fmt = '
plt.tight_layout()
```

```
-----------
Heat Map :-
-----------
```



Observation : Pclass and Fare show maximum relation.

Spliting Dataset into features and labels

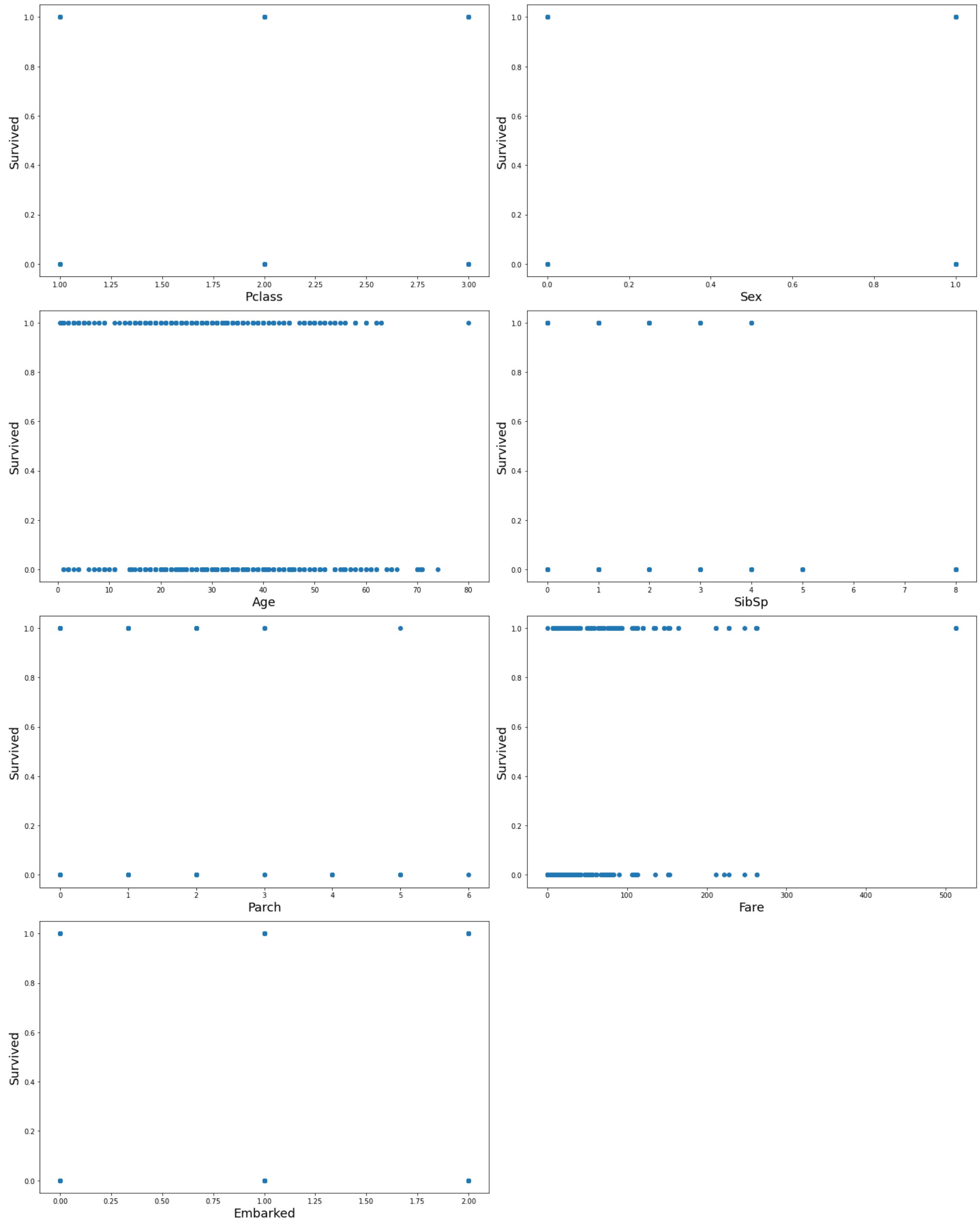
In [32]:
```
x = df.drop('Survived', axis = 1)
y = df.Survived
print('Data has been splited')
```

```
Data has been splited
```

In [33]:
```
# Let' see relation between features and labels.
print('------------------------')
print('Distribution Plot :-')
print('------------------------')

plt.figure(figsize = (20,25), facecolor = 'white')
plotnumber = 1
for column in x:
    if plotnumber <=8:
        ax = plt.subplot(4,2, plotnumber)
        plt.scatter(x[column],y)
        plt.xlabel(column, fontsize = 18)
        plt.ylabel('Survived', fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

```
------------------------
Distribution Plot :-
------------------------
```



Features are related to class

Checking skewnessm

In [34]:
```
x.skew()
```

Out[34]:
```
Pclass     -0.630548
Sex        -0.618921
Age         0.510245
SibSp       3.695352
Parch       2.749117
Fare        4.787317
Embarked   -1.264823
dtype: float64
```

Some feature has skewed

Data Scaling

In [35]:
```
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
x_scaled
```

Out[35]:
```
array([[ 0.82737724,  0.73769513, -0.56573646, ..., -0.47367361,
        -0.50244517,  0.58595414],
       [-1.56610693, -1.35557354,  0.66386103, ..., -0.47367361,
         0.78684529, -1.9423032 ],
       [ 0.82737724, -1.35557354, -0.25833709, ..., -0.47367361,
        -0.48885426,  0.58595414],
       ...,
       [ 0.82737724, -1.35557354, -0.1046374 , ...,  2.00893337,
        -0.17626324,  0.58595414],
       [-1.56610693,  0.73769513, -0.25833709, ..., -0.47367361,
        -0.04438104, -1.9423032 ],
       [ 0.82737724,  0.73769513,  0.20276197, ..., -0.47367361,
        -0.49237783, -0.67817453]])
```

Split data into train and test. Model will be bulit on training data and tested on test data

In [36]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, rando
print('Data has been splited.')
```

```
Data has been splited.
```

Model Building

Logistic Regression model instantiaing, training and evaluating

In [37]:
```python
Lr = LogisticRegression()
Lr.fit(x_train, y_train)
y_pred = Lr.predict(x_test)
```

In [38]:
```python
print('-----------------------------------------------------------\n')
print('Confusion Matrix :')
cfm = confusion_matrix(y_test, y_pred)
print(cfm)
print('\n-----------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-----------------------------------------------------------')
```

```
-----------------------------------------------------------

Confusion Matrix :
[[117  28]
 [ 24  54]]

-----------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.81      0.82       145
           1       0.66      0.69      0.68        78

    accuracy                           0.77       223
   macro avg       0.74      0.75      0.75       223
weighted avg       0.77      0.77      0.77       223

-----------------------------------------------------------
```

Conclusion : Logistic Regression model has 77% score

Cross Validation score to check if the model is overfitting

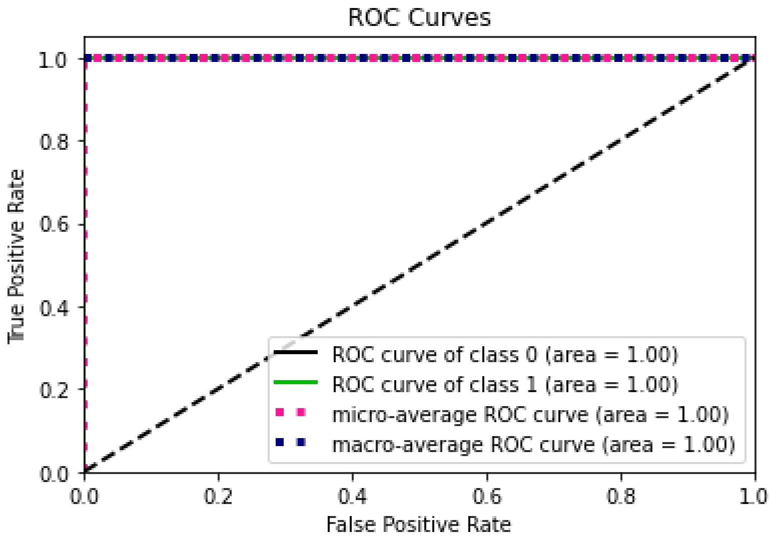
In [39]:
```python
cv = cross_val_score(Lr, x, y, cv = 5)
print('Cross Validation score of Logistic Regression model --->', cv.mean())
```

```
Cross Validation score of Logistic Regression model ---> 0.7890025735986442
```

Conclusion : Logistic Regression model has 78% Cross Validation score

ROC, AUC Curve

In [40]:
```
prob = Lr.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob)
plt.show()
```



Decision Tree model instantiaing, training and evaluating

In [41]:
```
DT = DecisionTreeClassifier()
DT.fit(x_train, y_train)
y_pred = DT.predict(x_test)
```

In [42]:
```
print('-------------------------------------------------------------\n')
print('Confusion Matrix :')
cfm = confusion_matrix(y_test, y_pred)
print(cfm)
print('\n-------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-------------------------------------------------------------')
```

```
-----------------------------------------------------------

Confusion Matrix :
[[106  39]
 [ 23  55]]

----------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.73      0.77       145
           1       0.59      0.71      0.64        78

    accuracy                           0.72       223
   macro avg       0.70      0.72      0.71       223
weighted avg       0.74      0.72      0.73       223

------------------------------------------------------------
```

Conclusion : Decision Tree model has 72% score .

Cross Validation score to check if the model is overfitting

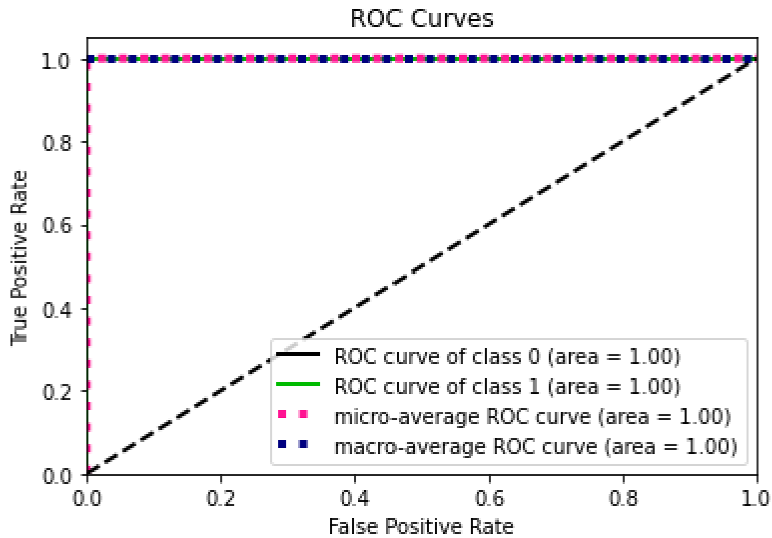
In [43]:
```
cv = cross_val_score(DT, x, y, cv = 5)
print('Cross Validation score of Decision Tree model --->', cv.mean())
```

```
Cross Validation score of Decision Tree model ---> 0.7822923859142553
```

Conclusion : Decision Tree model has 77% Cross Validation score

ROC, AUC Curve

In [44]:
```
prob = DT.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob)
plt.show()
```



Knn model instantiaing, training and evaluating

In [45]:
```
Knn = KNeighborsClassifier()
Knn.fit(x_train, y_train)
y_pred = Knn.predict(x_test)
```

In [46]:
```
print('------------------------------------------------------------\n')
print('Confusion Matrix :')
cfm = confusion_matrix(y_test, y_pred)
print(cfm)
print('\n------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------')
```

```
------------------------------------------------------------

Confusion Matrix :
[[110  35]
 [ 36  42]]

------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.76      0.76       145
           1       0.55      0.54      0.54        78

    accuracy                           0.68       223
   macro avg       0.65      0.65      0.65       223
weighted avg       0.68      0.68      0.68       223

------------------------------------------------------------
```

Conclusion : Knn model has 68% score

Cross Validation score to check if the model is overfitting

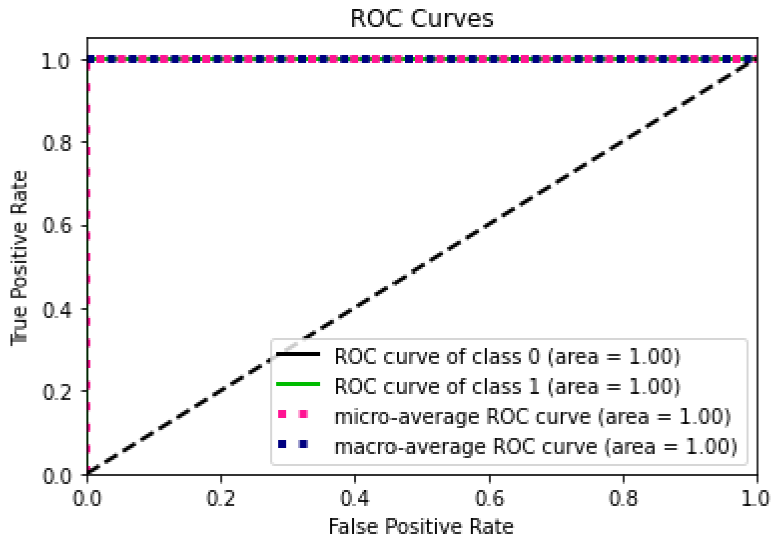
In [47]:
```
cv = cross_val_score(Knn, x, y, cv = 5)
print('Cross Validation score of Knn model --->', cv.mean())
```

```
Cross Validation score of Knn model ---> 0.6947649237336011
```

Conclusion : Knn model has 69% Cross Validation score

ROC, AUC Curve

In [48]:
```
prob = Knn.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob)
plt.show()
```



Random Forest model instantiaing, training and evaluating

In [49]:
```
Rn = RandomForestClassifier()
Rn.fit(x_train, y_train)
y_pred = Rn.predict(x_test)
```

In [50]:
```python
print('-------------------------------------------------------------\n')
print('Confusion Matrix :')
cfm = confusion_matrix(y_test, y_pred)
print(cfm)
print('\n-------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-------------------------------------------------------------')
```

```
-------------------------------------------------------------

Confusion Matrix :
[[111  34]
 [ 24  54]]

-------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.77      0.79       145
           1       0.61      0.69      0.65        78

    accuracy                           0.74       223
   macro avg       0.72      0.73      0.72       223
weighted avg       0.75      0.74      0.74       223

-------------------------------------------------------------
```

Conclusion : Random Forest model has 75% score

Cross Validation score to check if the model is overfitting

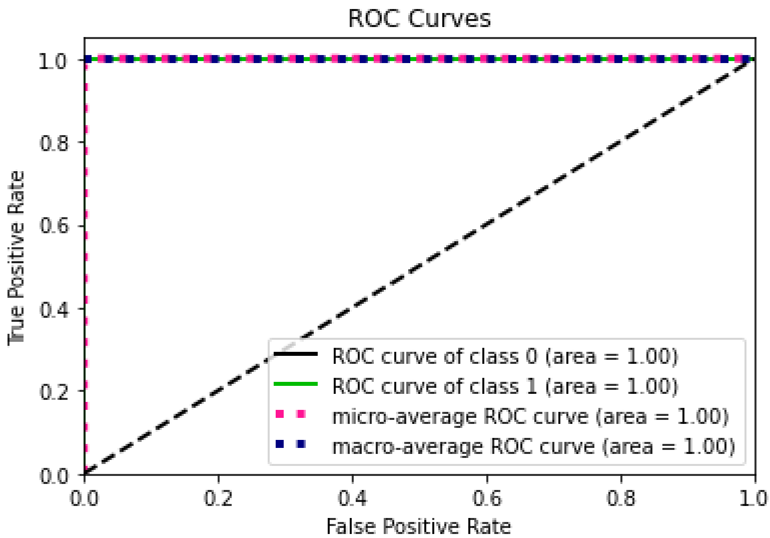
In [51]:
```python
cv = cross_val_score(Rn, x, y, cv = 5)
print('Cross Validation score of Random Forest model --->', cv.mean())
```

```
Cross Validation score of Random Forest model ---> 0.807005209967987
```

Conclusion : Random Forest model has 80% Cross Validation score .

ROC, AUC Curve

In [52]:
```
prob = Rn.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob)
plt.show()
```



SVM model instantiaing, training and evaluating

In [53]:
```
svc = SVC(probability=True)
svc.fit(x_train, y_train)
y_pred = svc.predict(x_test)
```

In [54]:
```
print('-----------------------------------------------------------\n')
print('Confusion Matrix :')
cfm = confusion_matrix(y_test, y_pred)
print(cfm)
print('\n-----------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-----------------------------------------------------------')
```

```
-----------------------------------------------------------

Confusion Matrix :
[[126  19]
 [ 57  21]]

----------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       0.69      0.87      0.77       145
           1       0.53      0.27      0.36        78

    accuracy                           0.66       223
   macro avg       0.61      0.57      0.56       223
weighted avg       0.63      0.66      0.62       223

------------------------------------------------------------
```

Conclusion : SVM model has 66% score

Cross Validation score to check if the model is overfitting

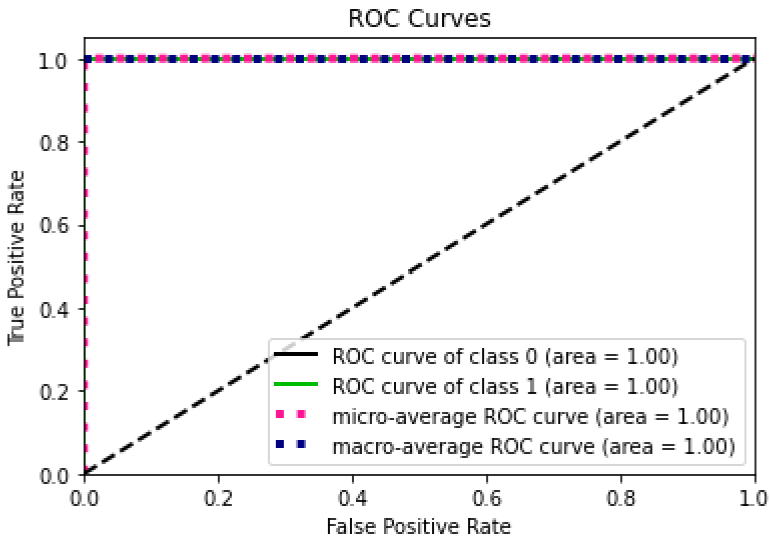
In [55]:
```
cv = cross_val_score(svc, x, y, cv = 5)
print('Cross Validation score of svc model --->', cv.mean())
```

```
Cross Validation score of svc model ---> 0.674615529470843
```

Conclusion : SVM model has 67% Cross Validation score

ROC, AUC Curve

In [56]:
```
prob = svc.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob)
plt.show()
```



Let's find ROC, AUC score

In [57]:
```
# LogisticRegression
roc_auc_score(y_test, Lr.predict(x_test))
```

Out[57]: 0.7496021220159151

In [58]:
```
# DecisionTreeClassifier
roc_auc_score(y_test, DT.predict(x_test))
```

Out[58]: 0.718081343943413

In [59]:
```
# RandomForestClassifier
roc_auc_score(y_test, Rn.predict(x_test))
```

Out[59]: 0.7289124668435013

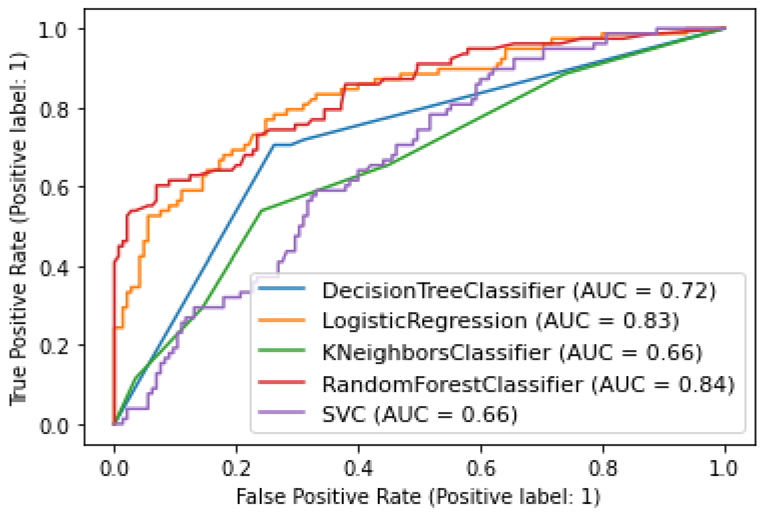
In [60]:
```
# KNeighborsClassifier
roc_auc_score(y_test, Knn.predict(x_test))
```

Out[60]: 0.6485411140583554

In [61]:
```
# SVMClassifier
roc_auc_score(y_test, svc.predict(x_test))
```
Out[61]:
```
0.5690981432360742
```

Let's check ROC, AUC Curve for the fitted model

In [62]:
```
disp = plot_roc_curve(DT, x_test, y_test)
plot_roc_curve(Lr, x_test, y_test, ax = disp.ax_) # ax_ = Axes with confusion mat
plot_roc_curve(Knn, x_test, y_test, ax = disp.ax_)
plot_roc_curve(Rn, x_test, y_test, ax = disp.ax_)
plot_roc_curve(svc, x_test, y_test, ax = disp.ax_)
plt.legend(prop = {'size':11}, loc = 'lower right')
plt.show()
```



Looking CV score we found Logistic Regression has best model so we do Hyperparameter Tuning on it.

In [63]:
```
param = { 'max_iter':[100],'penalty': ['l1','l2'],'fit_intercept':[True,False]}
```
In [64]:
```
grid_search = GridSearchCV(estimator = Lr, param_grid = param, cv = 5,n_jobs = -1
```
In [65]:
```
grid_search.fit(x_train, y_train)
```
Out[65]:
```
GridSearchCV(cv=5, estimator=LogisticRegression(), n_jobs=-1,
             param_grid={'fit_intercept': [True, False], 'max_iter': [100],
                         'penalty': ['l1', 'l2']})
```
In [66]:
```
best_parameters = grid_search.best_params_
print(best_parameters)
```
```
{'fit_intercept': False, 'max_iter': 100, 'penalty': 'l2'}
```

In [67]:
```
hlr = LogisticRegression(max_iter = 100, penalty = 'l2')
hlr.fit(x_train, y_train)
hlr.score(x_test, y_test)
```

Out[67]: 0.7668161434977578

In [68]:
```
y_pred = hlr.predict(x_test)
```

In [69]:
```
print('-----------------------------------------------------------\n')
print('Confusion Matrix :')
cfm = confusion_matrix(y_test, y_pred)
print(cfm)
print('\n-----------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-----------------------------------------------------------')
```

```
-----------------------------------------------------------

Confusion Matrix :
[[117  28]
 [ 24  54]]

-----------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.81      0.82       145
           1       0.66      0.69      0.68        78

    accuracy                           0.77       223
   macro avg       0.74      0.75      0.75       223
weighted avg       0.77      0.77      0.77       223

-----------------------------------------------------------
```

After Hyperparameter Tuning model accuracy score 77%

Saving The Model

In [70]:
```
# saving the model to the Local file system
filename = 'Titanic project.pickle'
pickle.dump(hlr, open(filename, 'wb'))
```

Final Conclusion : Logistic Regression is our best model.

In [ ]: