Titanic shipwreck

Who have survived?!

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The Challenge

The sinking of the Titanic is one of the most infamous shipwrecks in history.

On April 15, 1912, during her maiden voyage, the widely considered “unsinkable” RMS Titanic sank after colliding with an iceberg. Unfortunately, there weren’t enough lifeboats for everyone onboard, resulting in the death of 1502 out of 2224 passengers and crew.

While there was some element of luck involved in surviving, it seems some groups of people were more likely to survive than others.

In this challenge, we ask you to build a predictive model that answers the question: “what sorts of people were more likely to survive?” using passenger data (ie name, age, gender, socio-economic class, etc).

Content of our data:

Variable	Definition	Key
survival	Survival	0 = No, 1 = Yes
pclass	Ticket class	1 = 1st, 2 = 2nd, 3 = 3rd
sex	Sex	
Age	Age in years	
sibsp	# of siblings / spouses aboard the Titanic	
parch	# of parents / children aboard the Titanic	
ticket	Ticket number	
fare	Passenger fare	
cabin	Cabin number	
embarked	Port of Embarkation	C = Cherbourg, Q = Queenstown, S = Southampton

First : import all needed libraries and models

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.metrics import confusion_matrix,classification_report,accuracy_score,recall_score,precision_score,f1_score
from sklearn.preprocessing import StandardScaler,MinMaxScaler,RobustScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier , GradientBoostingClassifier
from sklearn.svm import SVC , LinearSVC
import xgboost as xgb
from imblearn.over_sampling import RandomOverSampler,SMOTE
from sklearn.feature_selection import RFE
from sklearn.ensemble import VotingClassifier
```

Second : data reading and preprocessing

[4]:

```
df=pd.read_csv('/kaggle/input/titanic/train.csv')
df.head(10)
```

[4]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	NaN	C

[7]:

```
df.drop(['PassengerId','Name','Ticket','Cabin'], axis=1, inplace=True)
print('----------------------------------------')
print(df.info())
print('----------------------------------------')
print(df.describe().T)
```

```
----------------------------------------
<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       714 non-null    float64
 4   SibSp     891 non-null    int64
 5   Parch     891 non-null    int64
 6   Fare      891 non-null    float64
 7   Embarked  889 non-null    object
dtypes: float64(2), int64(4), object(2)
memory usage: 55.8+ KB
None
----------------------------------------
          count       mean        std   min      25%      50%   75%       max
Survived  891.0   0.383838   0.486592  0.00   0.0000   0.0000   1.0    1.0000
Pclass    891.0   2.308642   0.836071  1.00   2.0000   3.0000   3.0    3.0000
Age       714.0  29.699118  14.526497  0.42  20.1250  28.0000  38.0   80.0000
SibSp     891.0   0.523008   1.102743  0.00   0.0000   0.0000   1.0    8.0000
Parch     891.0   0.381594   0.806057  0.00   0.0000   0.0000   0.0    6.0000
Fare      891.0  32.204208  49.693429  0.00   7.9104  14.4542  31.0  512.3292
```

Check and fill null values

In [3]:

```
print(df.info())
print('----------------------------------
--------')
print(df['Embarked'].unique())
print(df['Embarked'].value_counts())
print('----------------------------------
--------')
df['Embarked'].fillna(df['Embarked'].mod
e()[0],inplace=True)
print(df['Embarked'].value_counts())
print('----------------------------------
--------')
print(df['Age'].unique())
df['Age'].fillna(df.groupby(['Pclass','S
ex'])
['Age'].transform('mean'),inplace=True)
print('----------------------------------
--------')
print(df['Age'].unique())
print('----------------------------------
--------')
print(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    object
 3   Age       714 non-null    float64
 4   SibSp     891 non-null    int64
 5   Parch     891 non-null    int64
 6   Fare      891 non-null    float64
 7   Embarked  889 non-null    object
```

```
<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
```

Third : EDA and data visualization

(A)

In [4]:

```
stat=df.groupby('Sex')['Survived']
stat1 = stat.value_counts(normalize=False).reset_index(name='count')
print(stat1)
print('-------------------------------------')
stat2 = stat.value_counts(normalize=True).reset_index(name='count')
sns.barplot(x='Sex', y='count', hue='Survived', data=stat2,color='blue')
plt.title('Percentage of survived and died passengers from each gender')
plt.show()
```

```
      Sex  Survived  count
0  female         1    233
1  female         0     81
2    male         0    468
3    male         1    109
```

Total number of survived and died passengers from each gender:

-males survived=109

-males died=468

-females survived=233

-females died= 81

percentage of males survived from all males =18.9 %

percentage of females survived from all females =74.2 %

(B)

In [5]:

```
stat3=df.groupby('Pclass')['Survived']
stat4 = stat3.value_counts(normalize=False).reset_index(name='count')
print(stat4)
print('-------------------------------------')
stat5 = stat3.value_counts(normalize=True).reset_index(name='count')
sns.barplot(x='Pclass', y='count', hue='Survived', data=stat5,color='blue')
plt.title('Percentage of survived and died passengers from each Pclass')
plt.show()
```

```
   Pclass  Survived  count
0       1         1    136
1       1         0     80
2       2         0     97
3       2         1     87
4       3         0    372
5       3         1    119
```

Total number of survived and died passengers from each Pclass:

-Pclass(1): survived=136 , died=80

-Pclass(2): survived=87 , died=97

-Pclass(3): survived=119 , died=372

percentage of first class survived passengers from all first class passengers =62.9 %

percentage of second class survived passengers from all second class passengers =47.3 %

percentage of third class survived passengers from all third class passengers =24.2 %

(C)

```
stat6 = stat3.value_counts(normalize=True).reset_index(name='percentage')
stat6=stat6[stat6['Survived']==1]
plt.pie(stat6['percentage'],labels=stat6['Pclass'], autopct='%1.1f%%')
plt.title('percentage of each Pclass survived passengers from all survived passengers')
plt.show()
```

percentage of first class survived passengers from all survived passengers = 46.8 %

percentage of second class survived passengers from all survived passengers = 35.2 %

percentage of third class survived passengers from all survived passengers = 18 %

(D)

In [7]:

```
stat7=df.groupby('Embarked')['Survived']
stat8 = stat7.value_counts(normalize=False).reset_index(name='count')
print(stat8)
print('---------------------------------')
sns.countplot(data= df , x=df['Embarked'] , hue=df[ 'Survived'],color='blue')
plt.show()
```

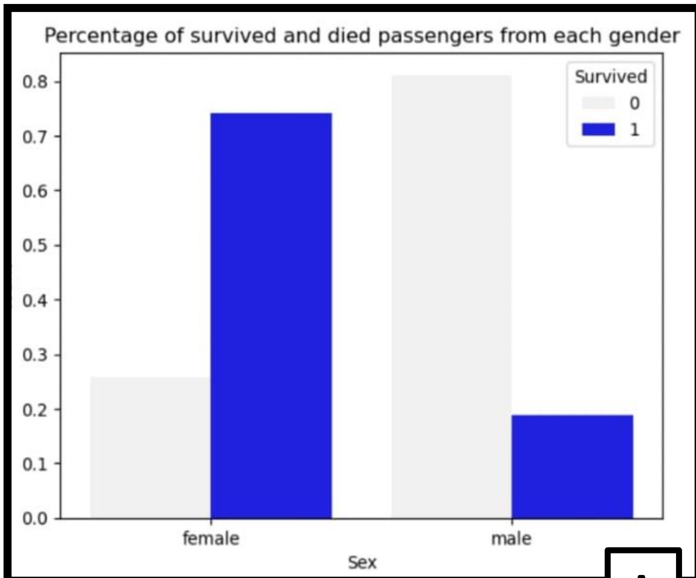
```
  Embarked  Survived  count
0        C         1     93
1        C         0     75
2        Q         0     47
3        Q         1     30
4        S         0    427
5        S         1    219
```

Total number of survived and died passengers from each Embarked port

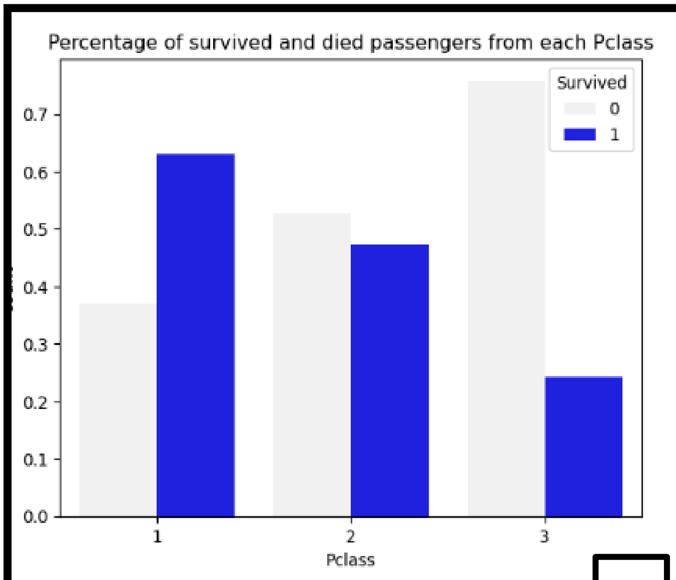
Embarked(C): survived=93 , died=75

Embarked(Q): survived=30 , died=47

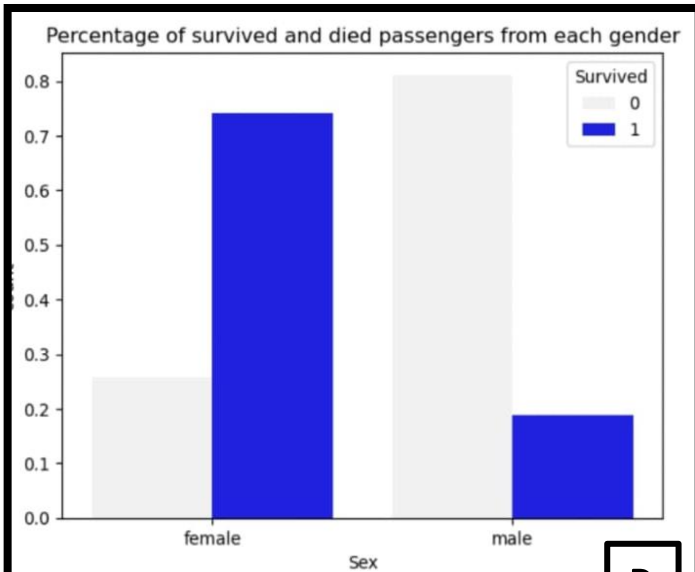
Embarked(S): survived=219 , died=427


Percentage of survived and died passengers from each gender
Survived
0
1
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
female
male
Sex

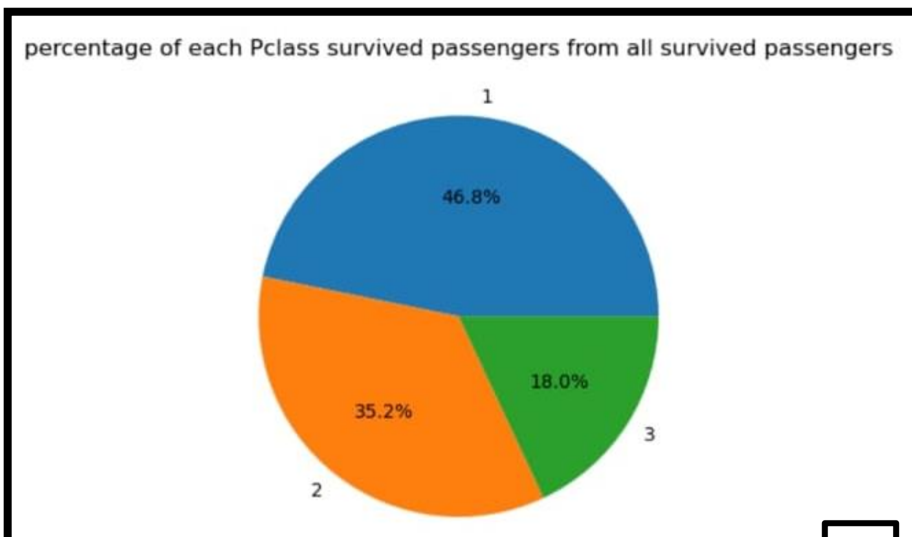
A


Percentage of survived and died passengers from each Pclass
Survived
0
1
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
1
2
3
Pclass

B


Percentage of survived and died passengers from each gender
Survived
0
1
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
female
male
Sex

D


percentage of each Pclass survived passengers from all survived passengers
1
46.8%
2
35.2%
3
18.0%

C

Encoding

In [8]:

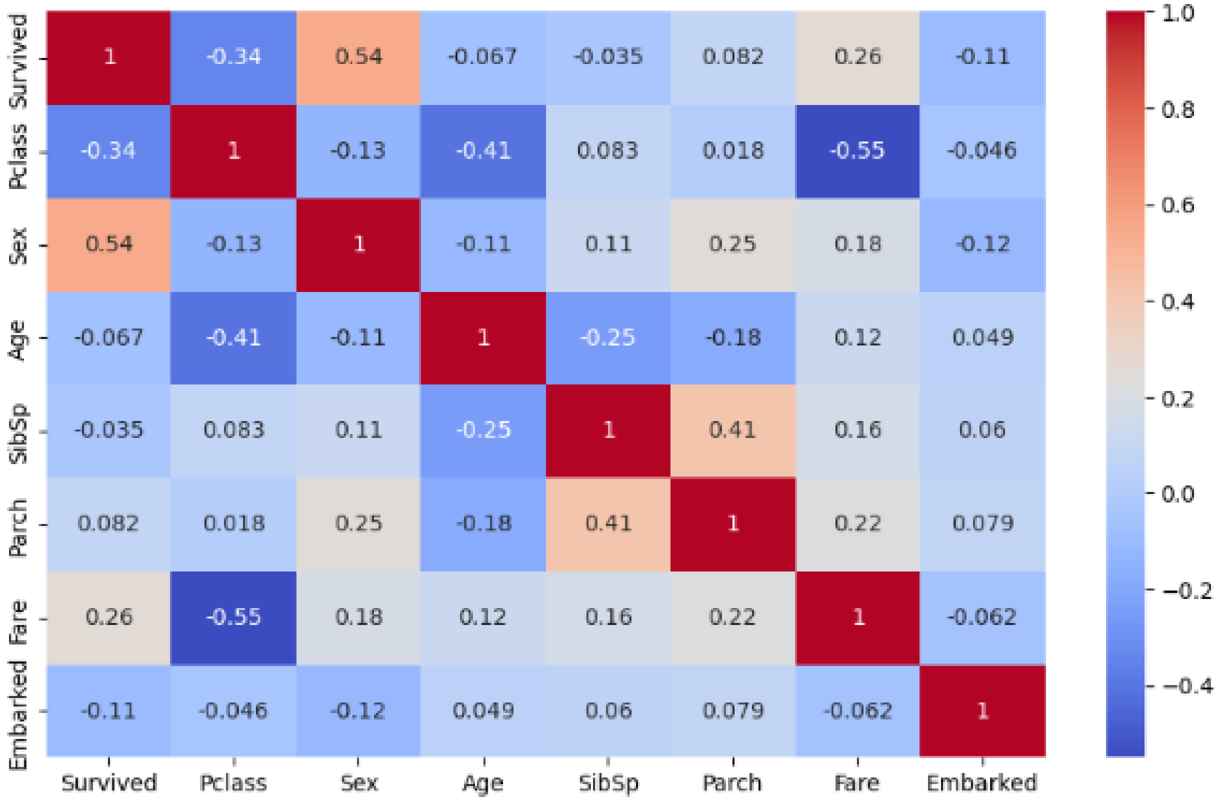
```
print(df['Sex'].unique())
print('transformed to')
df['Sex'] = [1 if i == 'female' else 0 f
or i in df['Sex']]
print(df['Sex'].unique())
print('---------------------------------
-')
print(df['Embarked'].unique())
print('transformed to')
df['Embarked'] = [2 if i == 'S' else 1 i
f i == 'C' else 0 for i in df['Embarke
d']]
print(df['Embarked'].unique())
print('---------------------------------
-')
print(df.head())
```

```
['male' 'female']
transformed to
[0 1]
----------------------------------
['S' 'C' 'Q']
transformed to
[2 1 0]
```

check correlation

In [9]:

```
df.corr()
fig, ax = plt.subplots(figsize=(10, 6))
sns.heatmap(df.corr(),annot=True, cmap='coolwarm')
```



Correlation conclusion:

- From all the above, we can conclude that females had greater chances of survival than males, in addition to being young in age, which gives you greater chances as well.

- Also, the chances of survival for passengers on the first Pclass were higher than others on the second and third Pclasses , and this was also affected by the fare , while the results were not greatly affected by the embarked or whether the passenger is accompanied by his family or not.

- So we need some engineering features to improve performance like divided ages to age categories and divided fare to fare categories and also combine all family members in one column describe the status of passenger if he was alone or not.

survival by age histogram

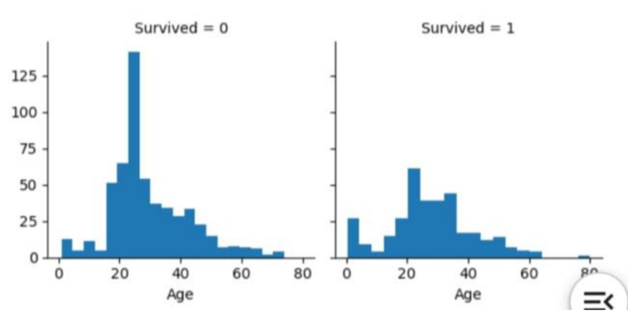
In [10]:

```
age_sur=df[['Age','Survived']]
young=(age_sur['Age'] < 6).sum()
age_sur_cond = ((age_sur['Age'] < 6) &
(age_sur['Survived'] ==1))
print(f'total number of survived children people is {age_sur_cond.sum()} out of
{young} , {age_sur_cond.sum()/young}%')
print('---------------------------------
--')
g = sns.FacetGrid(df, col = 'Survived')
g.map(plt.hist, 'Age', bins = 20)
```

```
total number of survived children people
is 31 out of 44 , 0.7045454545454546%
----------------------------------
```

Out[10]:

```
<seaborn.axisgrid.FacetGrid at 0x79f242c
a5ab0>
```

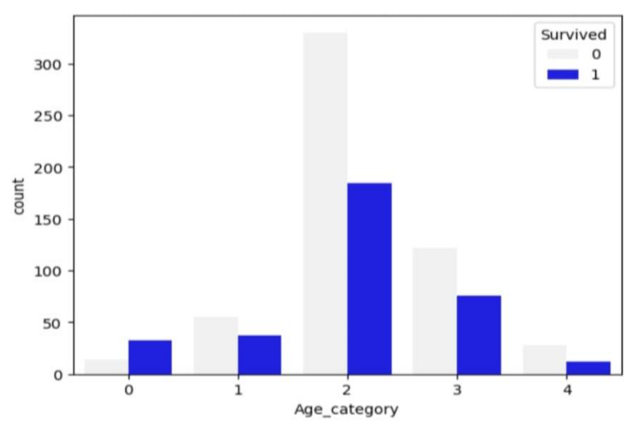


creating a new column 'Age_category' which is categorized based on age

In [11]:

```
df['Age_category']=pd.cut(df['Age'],bins
= [0, 6, 18, 35, 55, 100], labels = ['ba
by','child', 'Young Adult', 'Middle-Aged
Adult', 'Senior'])
df['Age_category'] = [4 if i == 'Senior'
else 3 if i =='Middle-Aged Adult' else 2
if i == 'Young Adult' else 1 if i == 'ch
ild'else 0 for i in df['Age_category']]
print(df['Age_category'].unique())
print('------------------------------')
sns.countplot(data= df , x=df['Age_categ
ory'] , hue=df[ 'Survived'],color='blu
e')
plt.show()
```

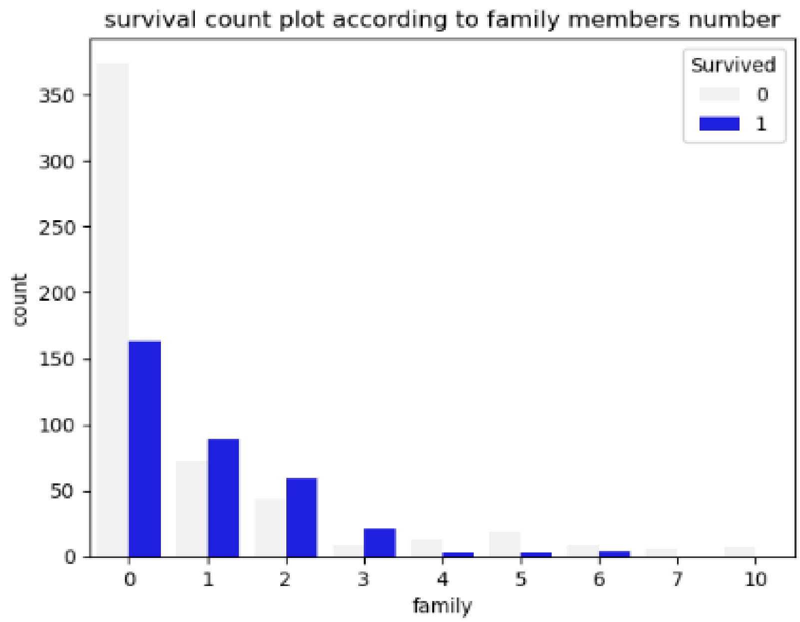
```
[2 3 0 1 4]
------------------------------
```

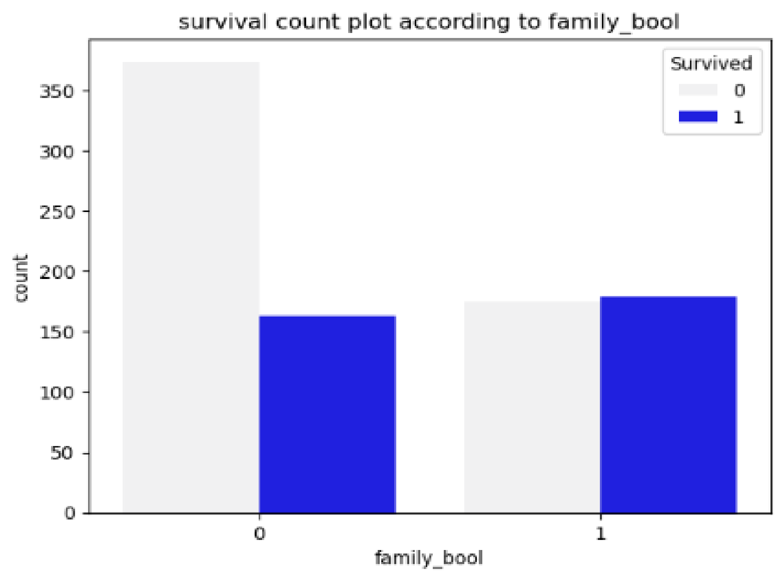


creating a new column 'Family' which is the sum of 'SibSp' and 'Parch' coulmns and new column 'family_bool' which represent the passengers are with family or alone

In [12]:

```
df['family'] = df['SibSp'] + df['Parch']
sns.countplot(data= df , x=df['family']
, hue=df[ 'Survived'],color='blue')
plt.title('survival count plot according
to family members number')
plt.show()
print('--------------------------')
df["family_bool"] = np.where(df["famil
y"] > 0, 1, 0)
sns.countplot(data= df , x=df['family_bo
ol'] , hue=df[ 'Survived'],color='blue')
plt.title('survival count plot according
to family_bool')
plt.show()
```

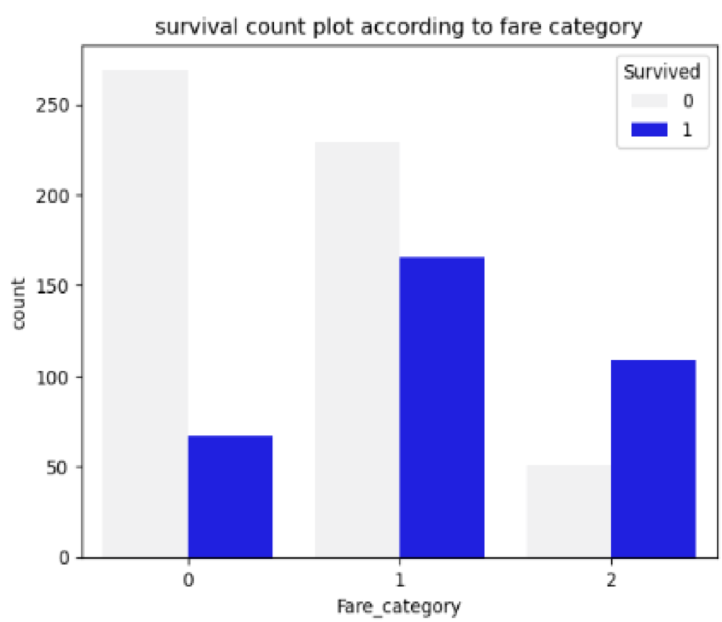




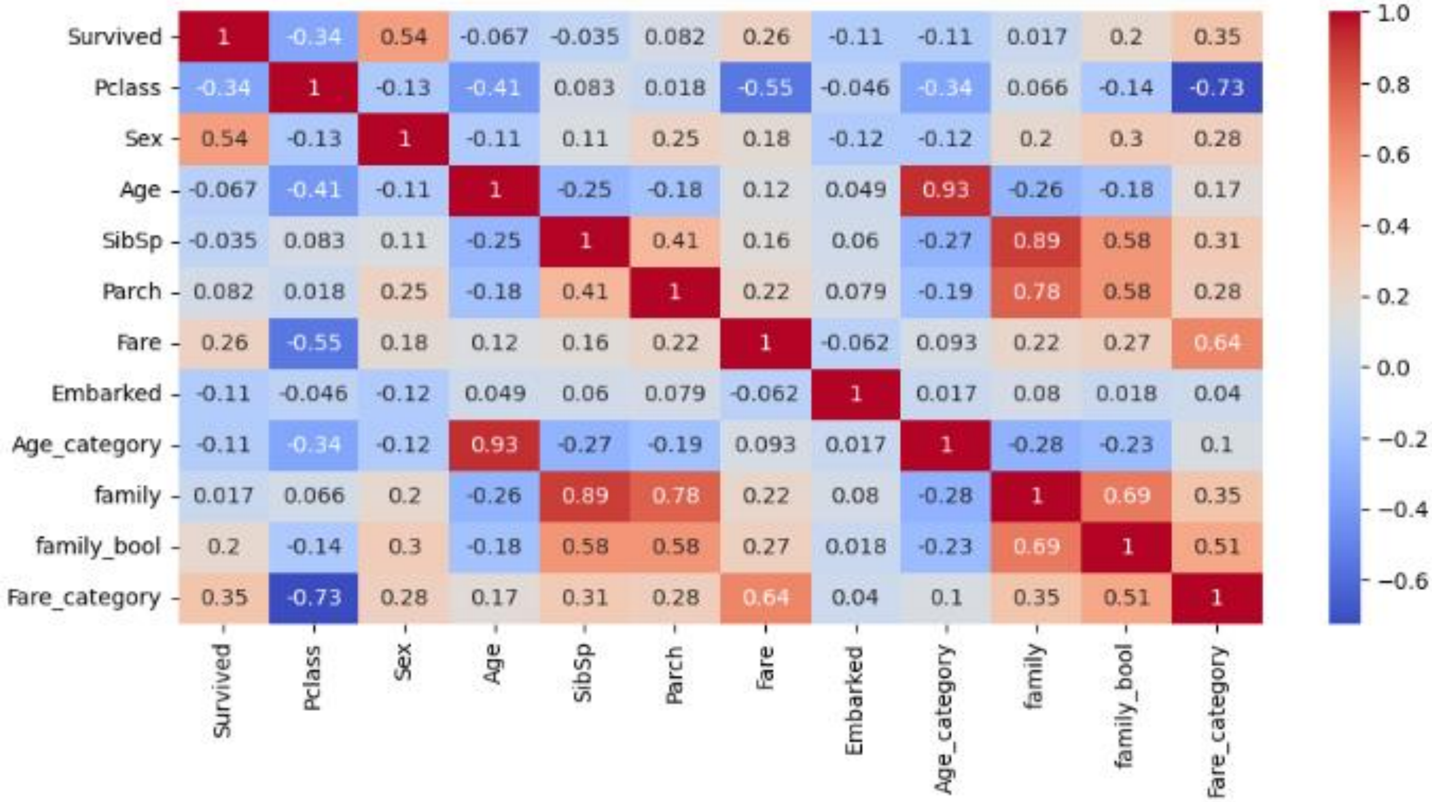
creating a new column classify passengers fare into three categories

In [13]:

```
df['Fare_category']=pd.cut(df['Fare'],bi
ns=[0,10,50,1000], labels=['low','mediu
m','high'])
df['Fare_category'] = [2 if i == 'high'
else 1 if i == 'medium' else 0 for i in
df['Fare_category']]
sns.countplot(data= df , x=df['Fare_cate
gory'] , hue=df[ 'Survived'],color='blu
e')
plt.title('survival count plot according
to fare category')
plt.show()
```



Check correlation between features again after preprocessing:



Split and scale data :

split data

In [15]:

```
x= df.drop(['Survived'], axis= 1)
y= df['Survived']
x_train,x_test,y_train,y_test=train_test
_split(x,y,test_size=.1,random_state=42)
x_train,x_val,y_train,y_val=train_test_s
plit(x_train,y_train,test_size=.1,random
_state=42)
```

scaling data

In [16]:

```
scaler=RobustScaler()
x_train=scaler.fit_transform(x_train)
x_val=scaler.transform(x_val)
x_test=scaler.transform(x_test)
```

We will use robust because of we had some outliers

Feature selection :

In [17]:

```
param_grid_1= {'n_features_to_select':
[1,2,3,4,5,6,7,8,9,10,11],'estimator__ma
x_depth': list(range(3,10)) ,
               'estimator__eta': [0.001,
0.01,0.1,1],'estimator__gamma': [0,.01,.
1,1,5,10]}
xg=xgb.XGBClassifier(objective="binary:l
ogistic", random_state=42)
wrapper = RFE(estimator=xg)
grid_search_1= GridSearchCV(estimator=wr
apper, param_grid=param_grid_1, scoring
='accuracy', cv=5, n_jobs=-1)
grid_search_1.fit(x_train, y_train)
print("Best hyperparameters:", grid_sear
ch_1.best_params_)
```

```
Best hyperparameters: {'estimator__eta':
0.1, 'estimator__gamma': 0.1, 'estimator
__max_depth': 5, 'n_features_to_select':
7}
```

In [18]:

```
xg=xgb.XGBClassifier(objective="binary:l
ogistic",random_state=42, max_depth= 5 ,
eta=0.1 , gamma= 0.1)
wrapper=RFE(xg,n_features_to_select=7)
wrapper.fit(x_train,y_train)

x_train_s=wrapper.transform(x_train)
x_val_s=wrapper.transform(x_val)
x_test_s=wrapper.transform(x_test)
mask = wrapper.get_support()
print(mask)
print('--------------------------------
----------------------')
x_train_s=pd.DataFrame(x_train_s)
x_val_s=pd.DataFrame(x_val_s)
x_test_s=pd.DataFrame(x_test_s)
print(x_train_s)
```

```
[ True  True  True  True False  True  Tr
ue False  True False False]
```

Fourth: build and tune some ML models on our selected data following these steps:

1- grid search to find best hyperparameters for models

2- fit model with best hyperparameters and check overfitting

3- model prediction and scores

A) random forest classifier

In [19]:

```
param_grid_RF= {'max_depth': list(range
(3,10)) ,'n_estimators': [50,100,200,40
0,500], 'criterion':['gini', 'entropy',
'log_loss']}
model_RF = RandomForestClassifier(bootst
rap=True ,random_state=42)
grid_search_RF = GridSearchCV(estimator=
model_RF,param_grid=param_grid_RF,scorin
g='accuracy',cv=5,n_jobs=-1)
grid_search_RF.fit(x_train_s, y_train)
print("Best hyperparameters:", grid_sear
ch_RF.best_params_)
```

```
Best hyperparameters: {'criterion': 'gin
i', 'max_depth': 7, 'n_estimators': 50}
```

In [20]:

```
RF_model=RandomForestClassifier(bootstra
p=True ,random_state=42,n_estimators= 50
, criterion='gini' , max_depth= 7)
RF_model.fit(x_train_s,y_train)
y_pred_RF_train=RF_model.predict(x_train
_s)
y_pred_RF_val=RF_model.predict(x_val_s)
accuracy_RF_train=accuracy_score(y_trai
n,y_pred_RF_train)
accuracy_RF_val=accuracy_score(y_val,y_p
red_RF_val)
print(f'train accuracy={accuracy_RF_trai
n * 100} %')
print('--------------------------------
-')
print(f'val accuracy={accuracy_RF_val* 1
00} %')
```

```
train accuracy=89.30555555555556 %
----------------------------------
val accuracy=87.65432098765432 %
```

In [21]:

```
y_pred_RF=RF_model.predict(x_test_s)
accuracy_RF=accuracy_score(y_test,y_pred
_RF)
recall_RF=recall_score(y_test,y_pred_RF)
precesion_RF=precision_score(y_test,y_pr
ed_RF)
f1_Score_RF=f1_score(y_test,y_pred_RF)
print(f'scores for random forest model f
or selected feature data')
print(f'accuracy={accuracy_RF * 100} %')
print(f'recall= {recall_RF * 100} %')
print(f'precision = {precesion_RF * 100}
%')
print(f'f1_score= {f1_Score_RF * 100}
%')
```

```
scores for random forest model for selec
ted feature data
accuracy=86.66666666666667 %
recall= 80.55555555555556 %
precision = 85.29411764705883 %
f1_score= 82.85714285714286 %
```

B) support vector machine classifier

In [22]:

```
param_grid_svm= {'C': [0.001 , 0.01,0.1,
1, 10 , 100],'kernel': ['linear','poly',
'rbf'] , 'degree' : [1,2,3,4,5,6,7]}
model_svm = SVC(random_state=42 , probab
ility=True)
grid_search_svm = GridSearchCV(estimator
=model_svm,param_grid=param_grid_svm,sco
ring='accuracy',cv=5,n_jobs=-1)
grid_search_svm.fit(x_train_s, y_train)
print("Best hyperparameters:", grid_sear
ch_svm.best_params_)
```

```
Best hyperparameters: {'C': 10, 'degre
e': 2, 'kernel': 'poly'}
```

In [23]:

```
svm_model=SVC(random_state=42,kernel='po
ly',C= 10 , degree=2)
svm_model.fit(x_train_s,y_train)
y_pred_svm_train=svm_model.predict(x_tra
in_s)
y_pred_svm_val=svm_model.predict(x_val_
s)
accuracy_svm_train=accuracy_score(y_trai
n,y_pred_svm_train)
accuracy_svm_val=accuracy_score(y_val,y_
pred_svm_val)
print(f'train accuracy ={accuracy_svm_tr
ain * 100} %')
print('---------------------------------
-------')
print(f'val accuracy ={accuracy_svm_val
* 100} %')
```

```
train accuracy =83.33333333333334 %
----------------------------------------
val accuracy =82.71604938271605 %
```

In [24]:

```
y_pred_svm=svm_model.predict(x_test_s)
accuracy_svm=accuracy_score(y_test,y_pre
d_svm)
recall_svm=recall_score(y_test,y_pred_sv
m)
precesion_svm=precision_score(y_test,y_p
red_svm)
f1_Score_svm=f1_score(y_test,y_pred_svm)
print(f'scores for svm')
print(f'accuracy ={accuracy_svm * 100}
%')
print(f'recall = {recall_svm * 100} %')
print(f'precision = {precesion_svm * 10
0} %')
print(f'f1_score= {f1_Score_svm * 100}
%')
```

```
scores for svm
accuracy =85.55555555555556 %
recall = 75.0 %
precision = 87.09677419354838 %
f1_score= 80.59701492537312 %
```

C) XG boosting

In [25]:

```
param_grid_xg= {'eta': [0.001,0.01,0.1,
0.2,0.4,0.6,0.8,1],'gamma': [0,.1,.5,1,
5,10,20,50,100] , 'max_depth':list(range
(3,10))}
model_xg = xgb.XGBClassifier(objective
="binary:logistic", random_state=42)
grid_search_xg = GridSearchCV(estimator=
model_xg,param_grid=param_grid_xg,scorin
g='accuracy',cv=5,n_jobs=-1)
grid_search_xg.fit(x_train_s, y_train)
print("Best hyperparameters:", grid_sear
ch_xg.best_params_)
```

```
Best hyperparameters: {'eta': 0.1, 'gamm
a': 1, 'max_depth': 5}
```

In [26]:

```
xg_model=xgb.XGBClassifier(objective="bi
nary:logistic",gamma=1, random_state=42,
max_depth= 5 , eta=0.1 )
xg_model.fit(x_train_s,y_train)
y_pred_xg_train=xg_model.predict(x_train
_s)
y_pred_xg_val=xg_model.predict(x_val_s)
accuracy_xg_train=accuracy_score(y_trai
n,y_pred_xg_train)
accuracy_xg_val=accuracy_score(y_val,y_p
red_xg_val)
print(f'train accuracy ={accuracy_xg_tra
in * 100} %')
print('---------------------------------
-------')
print(f'val accuracy ={accuracy_xg_val *
100} %')
```

```
train accuracy =88.88888888888889 %
----------------------------------------
val accuracy =79.01234567901234 %
```

In [27]:

```
y_pred_xg=xg_model.predict(x_test_s)
accuracy_xg=accuracy_score(y_test,y_pred
_xg)
recall_xg=recall_score(y_test,y_pred_xg)
precesion_xg=precision_score(y_test,y_pr
ed_xg)
f1_Score_xg=f1_score(y_test,y_pred_xg)
print(f'scores for xg')
print(f'accuracy ={accuracy_xg * 100}
%')
print(f'recall = {recall_xg * 100} %')
print(f'precision = {precesion_xg* 100}
%')
print(f'f1_score= {f1_Score_xg * 100}
%')
```

```
scores for xg
accuracy =84.44444444444444 %
recall = 83.33333333333334 %
precision = 78.94736842105263 %
f1_score= 81.08108108108108 %
```

D) gradient boosting

In [28]:

```
param_grid_gb= {'n_estimators': [50,100,
200,300,400,500,600 ,1000],'learning_rat
e': [0, 0.001,0.005,.01, 0.05,.1,.5,1,3,
5,10] , 'max_depth':list(range(3,15))}
model_gb = GradientBoostingClassifier(ra
ndom_state=42)
grid_search_gb = GridSearchCV(estimator=
model_gb,param_grid=param_grid_gb,scorin
g='accuracy',cv=5,n_jobs=-1)
grid_search_gb.fit(x_train_s, y_train)
print("Best hyperparameters:", grid_sear
ch_gb.best_params_)
```

```
Best hyperparameters: {'learning_rate':
0.005, 'max_depth': 5, 'n_estimators': 5
00}
```

In [29]:

```
gb_model=GradientBoostingClassifier(rand
om_state=42 ,n_estimators= 500 , learnin
g_rate= .005 , max_depth= 5)
gb_model.fit(x_train_s,y_train)
y_pred_gb_train=gb_model.predict(x_train
_s)
y_pred_gb_val=gb_model.predict(x_val_s)
accuracy_gb_train=accuracy_score(y_trai
n,y_pred_gb_train)
accuracy_gb_val=accuracy_score(y_val,y_p
red_gb_val)
print(f'train accuracy ={accuracy_gb_tra
in * 100} %')
print('---------------------------------
-------')
print(f'val accuracy ={accuracy_gb_val *
100} %')
```

```
train accuracy =90.55555555555556 %
----------------------------------------
val accuracy =80.24691358024691 %
```

In [30]:

```
y_pred_gb=gb_model.predict(x_test_s)
accuracy_gb=accuracy_score(y_test,y_pred
_gb)
recall_gb=recall_score(y_test,y_pred_gb)
precesion_gb=precision_score(y_test,y_pr
ed_gb)
f1_Score_gb=f1_score(y_test,y_pred_gb)
print(f'scores for gradient boosting')
print(f'accuracy ={accuracy_gb * 100}
%')
print(f'recall = {recall_gb * 100} %')
print(f'precision = {precesion_gb* 100}
%')
print(f'f1_score= {f1_Score_gb * 100}
%')
```

```
scores for gradient boosting
accuracy =84.44444444444444 %
recall = 77.77777777777779 %
precision = 82.35294117647058 %
f1_score= 80.0 %
```

E) logistic regression

In [31]:

```
param_grid_LR= {'C' : [.001, .01, .1 ,
1, 10] }
model_LR = LogisticRegression(random_sta
te=42 , penalty ='l2')
grid_search_LR = GridSearchCV(estimator=
model_LR,param_grid=param_grid_LR,scorin
g='accuracy',cv=5,n_jobs=-1)
grid_search_LR.fit(x_train_s, y_train)
print("Best hyperparameters:", grid_sear
ch_LR.best_params_)
```

```
Best hyperparameters: {'C': 0.1}
```

In [32]:

```
LR_model=LogisticRegression(random_state
=42 , penalty ='l2', C=0.1 )
LR_model.fit(x_train_s,y_train)
y_pred_LR_train=LR_model.predict(x_train
_s)
y_pred_LR_val=LR_model.predict(x_val_s)
accuracy_LR_train=accuracy_score(y_trai
n,y_pred_LR_train)
accuracy_LR_val=accuracy_score(y_val,y_p
red_LR_val)
print(f' train accuracy={accuracy_LR_tra
in * 100} %')
print('--------------------------------
-------')
print(f' val accuracy={accuracy_LR_val *
100} %')
```

```
 train accuracy=80.69444444444444 %
---------------------------------------
 val accuracy=80.24691358024691 %
```

In [33]:

```
y_pred_LR=LR_model.predict(x_test_s)
accuracy_LR=accuracy_score(y_test,y_pred
_LR)
recall_LR=recall_score(y_test,y_pred_LR)
precesion_LR=precision_score(y_test,y_pr
ed_LR)
f1_Score_LR=f1_score(y_test,y_pred_LR)
print(f'scores for logistic regression m
odel')
print(f'accuracy={accuracy_LR * 100} %')
print(f'recall= {recall_LR * 100} %')
print(f'precision = {precesion_LR * 100}
%')
print(f'f1_score= {f1_Score_LR * 100}
%')
```

```
scores for logistic regression model
accuracy=88.88888888888889 %
recall= 86.11111111111111 %
precision = 86.11111111111111 %
f1_score= 86.11111111111111 %
```

F) Voting between all previous models

In [34]:

```
hard_voting = VotingClassifier(estimators=[('rf',RF_model),('gb', gb_model) ,('lr',LR_model ) ,('xg',xg_model ) ,  ('svm',svm_model )], voting='hard')
hard_voting.fit(x_train_s, y_train)
y_pred_hv_train=hard_voting.predict(x_train_s)
y_pred_hv_val=hard_voting.predict(x_val_s)
accuracy_hv_train=accuracy_score(y_train,y_pred_hv_train)
accuracy_hv_val=accuracy_score(y_val,y_pred_hv_val)
print(f' train accuracy={accuracy_hv_train * 100} %')
print('----------------------------------------')
print(f' val accuracy={accuracy_hv_val * 100} %')
```

```
 train accuracy=88.33333333333333 %
----------------------------------------
 val accuracy=86.41975308641975 %
```

In [35]:

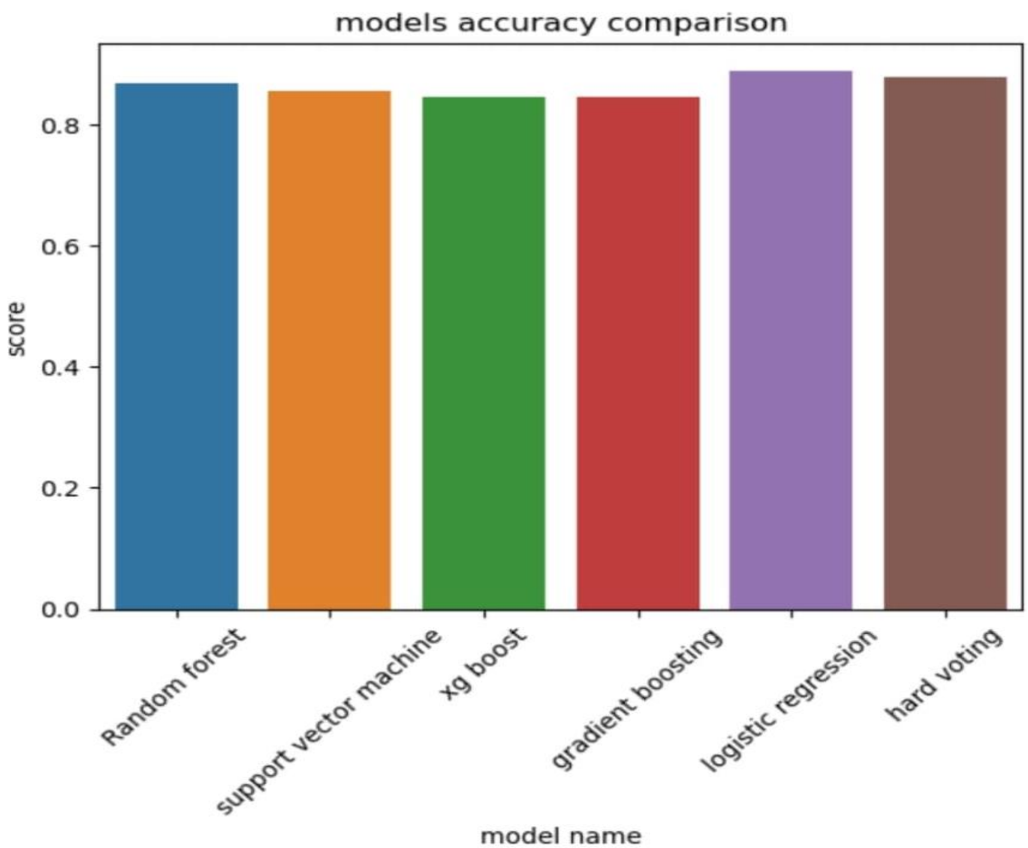
```
y_pred_hv=hard_voting.predict(x_test_s)
accuracy_hv=accuracy_score(y_test,y_pred_hv)
recall_hv=recall_score(y_test,y_pred_hv)
precesion_hv=precision_score(y_test,y_pred_hv)
f1_Score_hv=f1_score(y_test,y_pred_hv)
print(f'scores for hard voting model')
print(f'accuracy={accuracy_hv * 100} %')
print(f'recall= {recall_hv * 100} %')
print(f'precision = {precesion_hv * 100} %')
print(f'f1_score= {f1_Score_hv * 100} %')
```

```
scores for hard voting model
accuracy=87.77777777777777 %
recall= 83.33333333333334 %
precision = 85.71428571428571 %
f1_score= 84.50704225352112 %
```

models comparison

In [36]:

```
models_names=['Random forest','support v
ector machine','xg boost','gradient boos
ting','logistic regression', 'hard votin
g']
model_accuracies=[accuracy_RF,accuracy_s
vm ,accuracy_xg ,accuracy_gb ,accuracy_L
R , accuracy_hv ]
sns.barplot(x=models_names, y=model_accu
racies)
plt.xlabel('model name')
plt.ylabel('score')
plt.title('models accuracy comparison')
plt.xticks(rotation=45)
plt.show()
```



Fifth: test data preprocessing and submit on kaggle to make an actual test for our models

Test data preprocessing

In [37]:

```
test_data = pd.read_csv("/kaggle/input/titanic/test.csv")
passID_test=test_data.PassengerId
test_data['Embarked'].fillna(test_data['Embarked'].mode()[0],inplace=True)
test_data['Age'].fillna(test_data.groupby(['Pclass','Sex'])['Age'].transform('mean'),inplace=True)

test_data['Sex'] = [1 if i == 'female' else 0 for i in test_data['Sex']]
test_data['Embarked'] = [2 if i == 'S' else 1 if i == 'C' else 0 for i in test_data['Embarked']]
test_data['Age_category']=pd.cut(test_data['Age'],bins = [0, 6, 18, 35, 55, 100], labels = ['baby','child', 'Young Adult', 'Middle-Aged Adult', 'Senior'])
test_data['Age_category'] = [4 if i == 'Senior' else 3 if i =='Middle-Aged Adult' else 2 if i == 'Young Adult' else 1 if i == 'child'else 0 for i in test_data['Age_category']]
test_data['family'] = test_data['SibSp'] + test_data['Parch']
test_data["family_bool"] = np.where(test_data["family"] > 0, 1, 0)
test_data['Fare_category']=pd.cut(test_data['Fare'],bins=[0,10,50,1000], labels=['low','medium','high'])
test_data['Fare_category'] = [2 if i == 'high' else 1 if i == 'medium' else 0 for i in test_data['Fare_category']]
print(test_data.head())
print('-------------------------------------------')
print(test_data.info())
print('-------------------------------------------')
print(test_data[test_data['Fare'].isna()].index)
print(test_data.iloc[152])
test_data['Fare'].fillna(8 ,inplace=True) #according to other features of passenger

test_s=pd.DataFrame(test_data)[['Pclass', 'Sex', 'Age','SibSp', 'Fare','Embarked','family' ]]
test_s=scaler.fit_transform(test_s)
```

Submit models separately on kaggle competition to get actual scores:

In [38]:

```
# Random forest
#y_test_RF=RF_model.predict(test_s)
#subDF=pd.DataFrame({'PassengerId':passID
_test, 'Survived':y_test_RF})
#subDF.to_csv("submission.csv", index=Fal
se)
# kaggle score=.78708
```

In [39]:

```
# SVM
#y_test_svm=svm_model.predict(test_s)
#subDF=pd.DataFrame({'PassengerId':passID
_test, 'Survived':y_test_svm})
#subDF.to_csv("submission.csv", index=Fal
se)
# kaggle score=.75119
```

In [40]:

```
# XG boost
#y_test_xg=xg_model.predict(test_s)
#subDF=pd.DataFrame({'PassengerId':passID
_test, 'Survived':y_test_xg})
#subDF.to_csv("submission.csv", index=Fal
se)
# kaggle score=.74641
```

In [41]:

```
# gradient boosting
#y_test_gb=gb_model.predict(test_s)
#subDF=pd.DataFrame({'PassengerId':passID
_test, 'Survived':y_test_gb})
#subDF.to_csv("submission.csv", index=Fal
se)
# kaggle score=.78947
```

In [42]:

```
# logistic regression
#y_test_LR=LR_model.predict(test_s)
#subDF=pd.DataFrame({'PassengerId':passID
_test, 'Survived':y_test_LR})
#subDF.to_csv("submission.csv", index=Fal
se)
# kaggle score=.76315
```

In [43]:

```
# hard_voting
#y_test_hv=hard_voting .predict(test_s)
#subDF=pd.DataFrame({'PassengerId':passID
_test, 'Survived':y_test_hv})
#subDF.to_csv("submission.csv", index=Fal
se)
# kaggle score = .77751
```

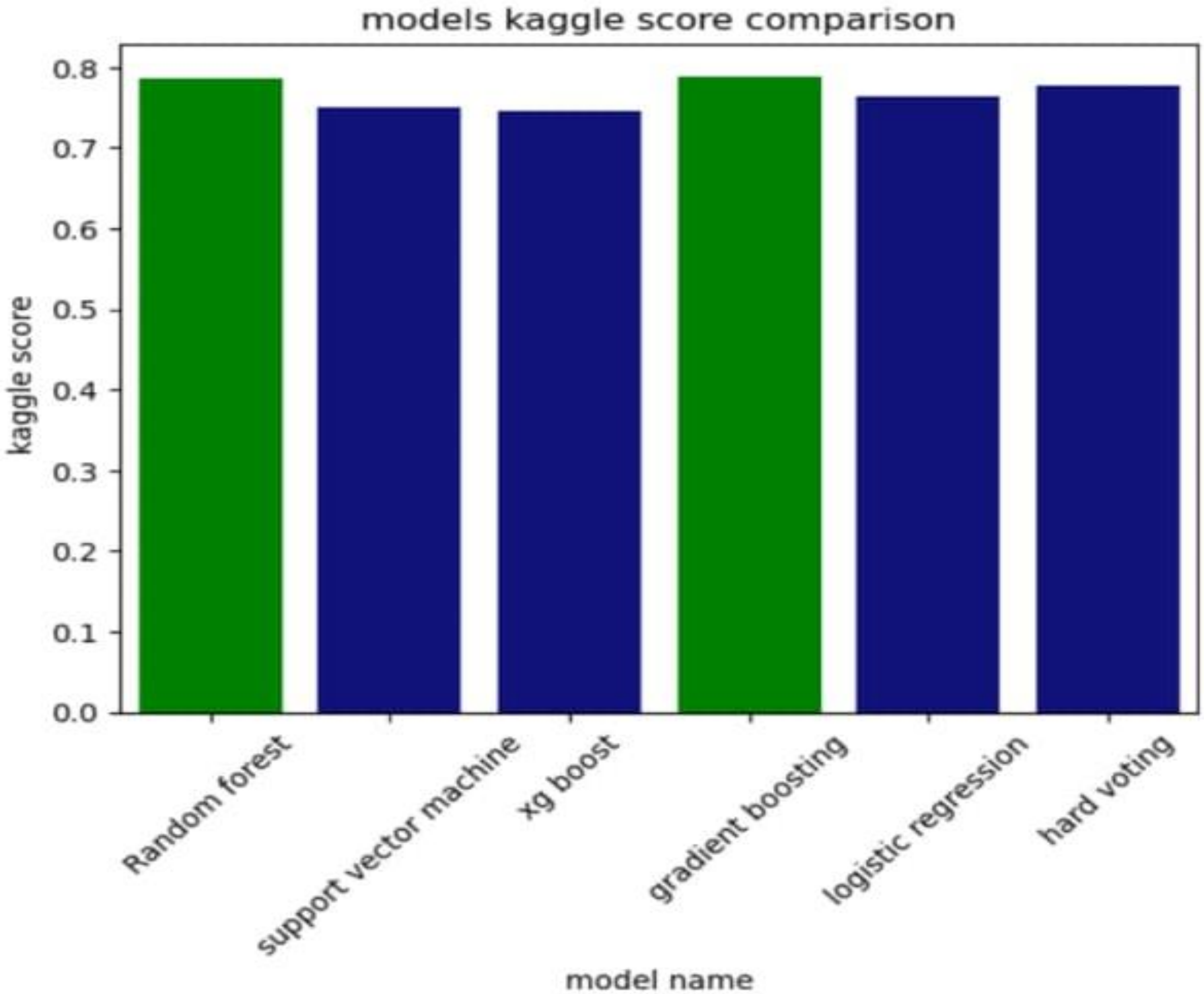
kaggle scores comparison

In [44]:

```
models_names=['Random forest','support v
ector machine','xg boost','gradient boos
ting','logistic regression', 'hard votin
g']
models_kag_scores=[.78708 ,.75119 ,.7464
1, .78947 , .76315  ,.77751]
```

In [45]:

```
bar=sns.barplot(x=models_names, y=models
_kag_scores, color='darkblue')
bar.patches[3].set_facecolor('green')
bar.patches[0].set_facecolor('green')
plt.xlabel('model name')
plt.ylabel(' kaggle score')
plt.title('models kaggle score compariso
n')
plt.xticks(rotation=45)
plt.show()
```



<u>Conclusion:</u>

-The best model that performed with our data is the gradient boosting model and this was with a slight difference from the random forest model.

-The voting model which depends on fit more than one model then make voting between them achieved good results also.

-while the logistic regression model was a little far away although it was giving good results with the already existing data (train, validation , test) But it seems that were a deceptive results, and the same was true for the support vector machine model and xg boosting model.

- the best two models performances with our data were gradient boosting and random forest , so what about make a voting between both of them only and check the results ?

In [46]:

```
final_soft_voting = VotingClassifier(estimators=[('rf',RF_model),('gb', gb_model) ], voting='soft' ,)
final_soft_voting.fit(x_train_s, y_train)
y_pred_sv_train=final_soft_voting.predict(x_train_s)
y_pred_sv_val=final_soft_voting.predict(x_val_s)
accuracy_sv_train=accuracy_score(y_train,y_pred_sv_train)
accuracy_sv_val=accuracy_score(y_val,y_pred_sv_val)
print(f' train accuracy={accuracy_sv_train * 100} %')
print(f' val accuracy={accuracy_sv_val * 100} %')
```

```
train accuracy=90.55555555555556 %
val accuracy=82.71604938271605 %
```

In [47]:

```
y_pred_sv=final_soft_voting.predict(x_test_s)
accuracy_sv=accuracy_score(y_test,y_pred_sv)
recall_sv=recall_score(y_test,y_pred_sv)
precesion_sv=precision_score(y_test,y_pred_sv)
f1_Score_sv=f1_score(y_test,y_pred_sv)
print(f'scores for hard voting model')
print(f'accuracy={accuracy_sv * 100} %')
print(f'recall= {recall_sv * 100} %')
print(f'precision = {precesion_sv * 100} %')
print(f'f1_score= {f1_Score_sv * 100} %')
```

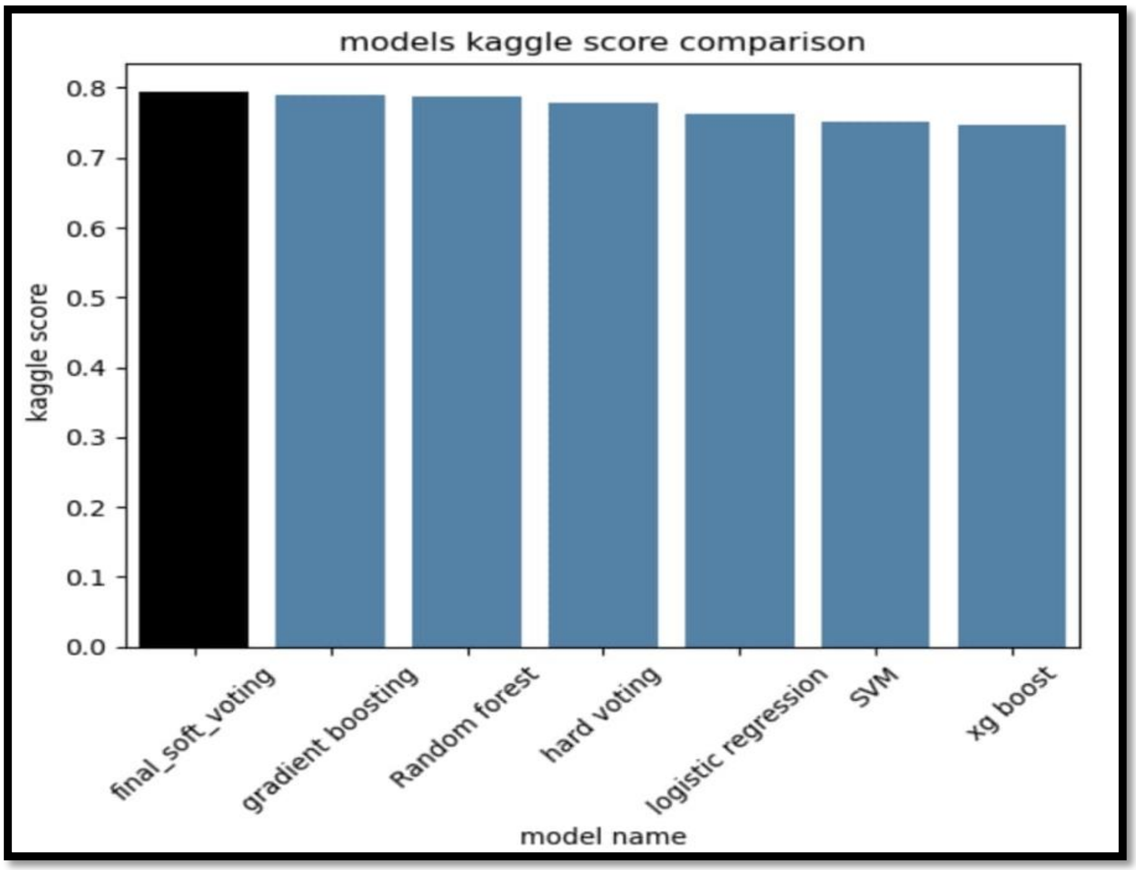
```
scores for hard voting model
accuracy=85.55555555555556 %
recall= 77.77777777777779 %
precision = 84.84848484848484 %
f1_score= 81.15942028985506 %
```

```
#final_soft_voting
y_test_sv=final_soft_voting.predict(test_s)
subDF=pd.DataFrame({'PassengerId':passID_test, 'Survived':y_test_sv})
subDF.to_csv("submission.csv", index=False)
# kaggle score = .79425
```

kaggle scores for all models in descending order

In [49]:

```
models_names=['final_soft_voting','gradient boosting','Random forest','hard voting','logistic regression','SVM','xg boost']
models_kag_scores=[ .79425,.78947 , .78708 ,.77751 , .76315 , .75119 ,.74641  ]
a=sns.barplot(x=models_names, y=models_kag_scores ,color='steelblue')
a.patches[0].set_facecolor('black')
plt.xlabel('model name')
plt.ylabel(' kaggle score')
plt.title('models kaggle score comparison')
plt.xticks(rotation=45)
plt.show()
```



Thanks if you have continued till here....