HEALTHCARE ANALYSIS

importing necessary libraries

In [44]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('ggplot')
import seaborn as sns
sns.set(rc={'figure.figsize':(10,8)})
sns.set_style("white")
sns.set_context({"figure.figsize": (10, 8)})
from sklearn.model_selection import train_test_split, cross_val_score, KFold, GridSe
from sklearn.preprocessing import StandardScaler
from imblearn.combine import SMOTETomek
from sklearn.metrics import classification_report, confusion_matrix
import warnings
warnings.filterwarnings('ignore')
```

In [4]:
```
print(plt.style.available)
```

```
['Solarize_Light2', '_classic_test_patch', 'bmh', 'classic', 'dark_background', 'fas
t', 'fivethirtyeight', 'ggplot', 'grayscale', 'seaborn', 'seaborn-bright', 'seaborn-
colorblind', 'seaborn-dark', 'seaborn-dark-palette', 'seaborn-darkgrid', 'seaborn-de
ep', 'seaborn-muted', 'seaborn-notebook', 'seaborn-paper', 'seaborn-pastel', 'seabor
n-poster', 'seaborn-talk', 'seaborn-ticks', 'seaborn-white', 'seaborn-whitegrid', 't
ableau-colorblind10']
```

read data

In [2]:
```
data=pd.read_csv('health care diabetes.csv')
```

In [3]:
```
data.head()
```

Out[3]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
0	6	148	72	35	0	33.6	0.627	5(
1	1	85	66	29	0	26.6	0.351	31
2	8	183	64	0	0	23.3	0.672	32
3	1	89	66	23	94	28.1	0.167	21
4	0	137	40	35	168	43.1	2.288	33

In [4]:
```
data.isna().sum()
```

Out[4]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
```

```
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [5]:
```
lst=['Glucose','BloodPressure','SkinThickness','Insulin','BMI']
```

In [ ]:
```
si_median=SimpleImputer(missing_values=0, strategy='median')
```

In [7]:
```
data.describe()
```

Out[7]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedi
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

In [8]:
```
for col in lst:
    data[col]=data[col].replace(0, np.nan)
```

In [9]:
```
data.isna().sum()
```

Out[9]:
```
Pregnancies                   0
Glucose                       5
BloodPressure                35
SkinThickness               227
Insulin                     374
BMI                          11
DiabetesPedigreeFunction      0
Age                           0
Outcome                       0
dtype: int64
```

In [10]:
```
for col in lst:
    if col=='Insulin':
        data[col]=data[col].fillna(data[col].mean())
    else:
        data[col]=data[col].fillna(data[col].median())
```

In [11]:
```
data.isna().sum()
```

Out[11]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
```

```
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [12]:

```
data.describe()
```

Out[12]:

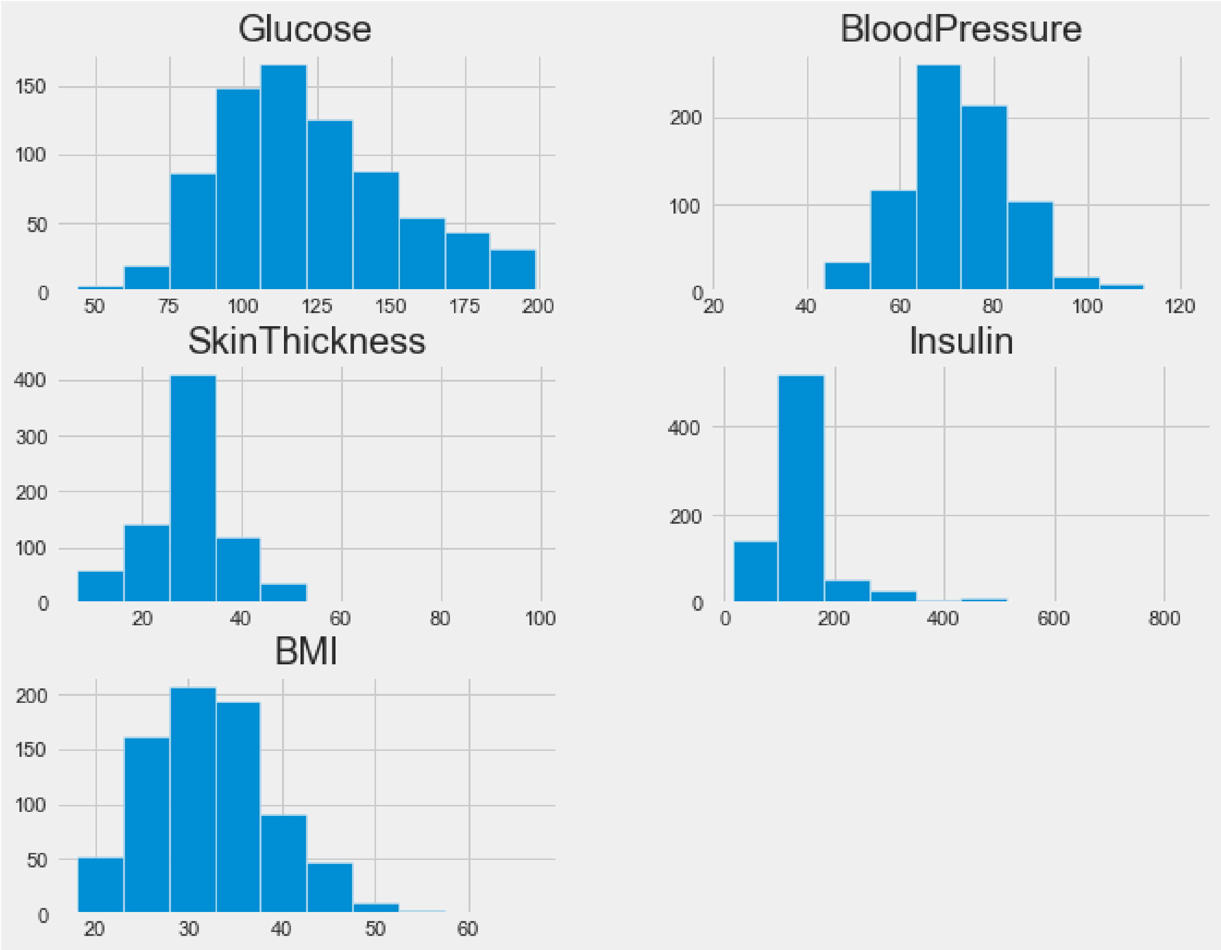
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedig
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	121.656250	72.386719	29.108073	155.548223	32.455208	
std	3.369578	30.438286	12.096642	8.791221	85.021108	6.875177	
min	0.000000	44.000000	24.000000	7.000000	14.000000	18.200000	
25%	1.000000	99.750000	64.000000	25.000000	121.500000	27.500000	
50%	3.000000	117.000000	72.000000	29.000000	155.548223	32.300000	
75%	6.000000	140.250000	80.000000	32.000000	155.548223	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

In [29]:

```
plt.style.use('fivethirtyeight')
data[lst].hist()
```

Out[29]:

```
array([[<AxesSubplot:title={'center':'Glucose'}>,
        <AxesSubplot:title={'center':'BloodPressure'}>],
       [<AxesSubplot:title={'center':'SkinThickness'}>,
        <AxesSubplot:title={'center':'Insulin'}>],
       [<AxesSubplot:title={'center':'BMI'}>, <AxesSubplot:>]],
      dtype=object)
```

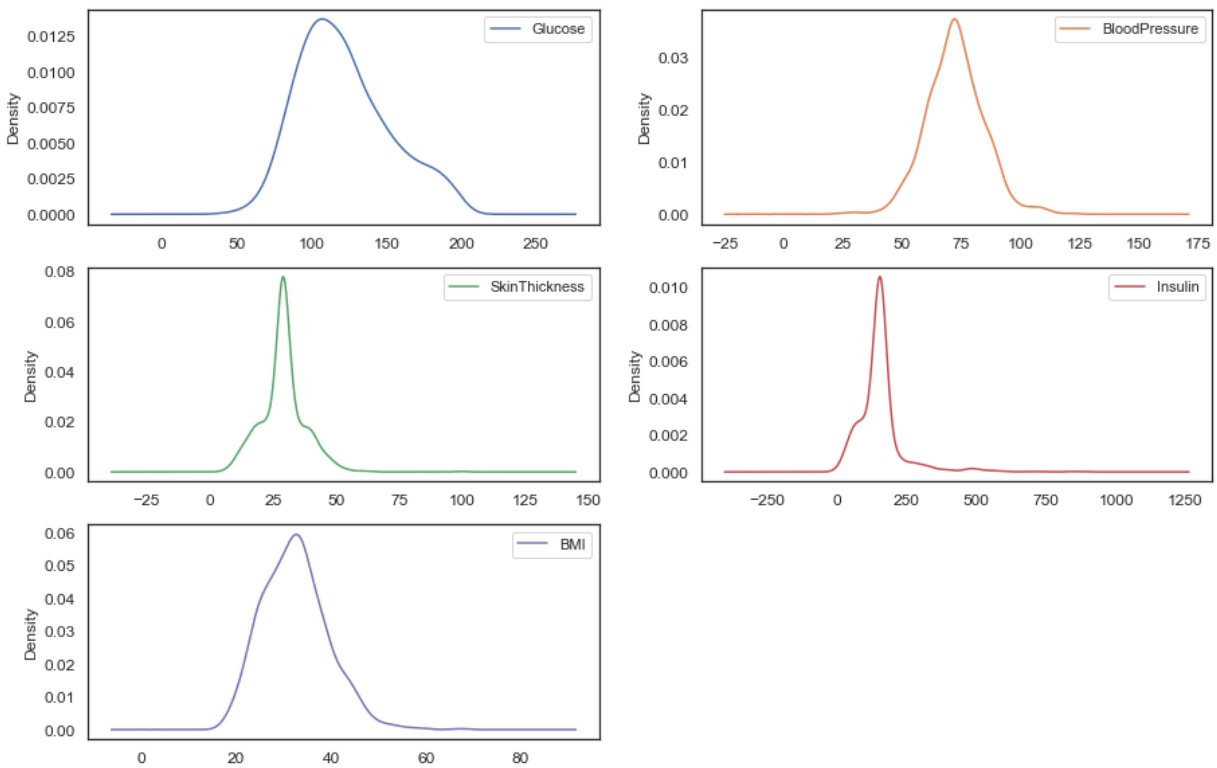


In [17]:

```
data[lst].plot(kind= 'density', subplots=True, layout=(3,2), sharex=False,
                     sharey=False,fontsize=12, figsize=(15,10))
```

Out[17]:

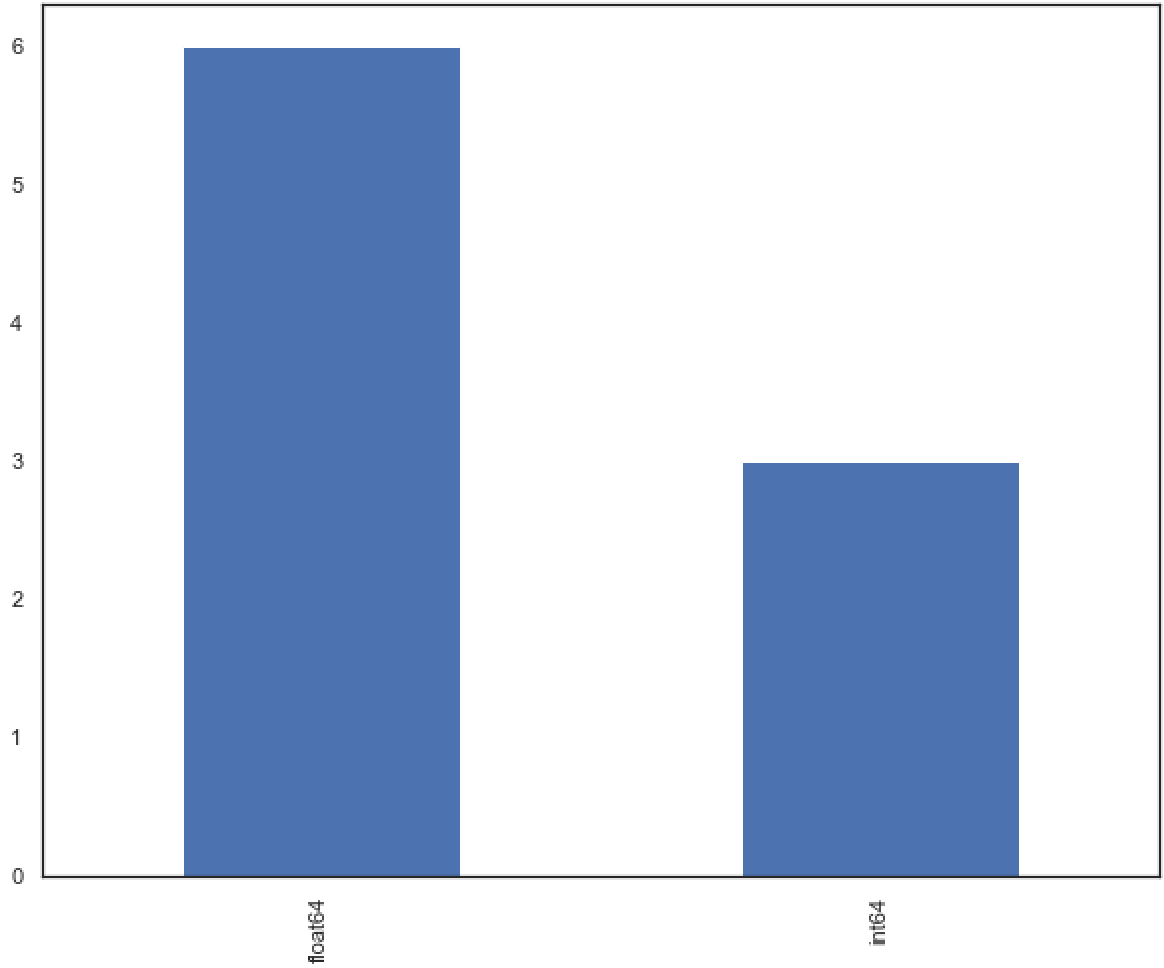
```
array([[<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>],
       [<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>],
       [<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>]],
      dtype=object)
```



In [14]:

```
data.dtypes.value_counts().plot.bar()
```

Out[14]: <AxesSubplot:>



In [15]:

```
data['Outcome'].value_counts()
```

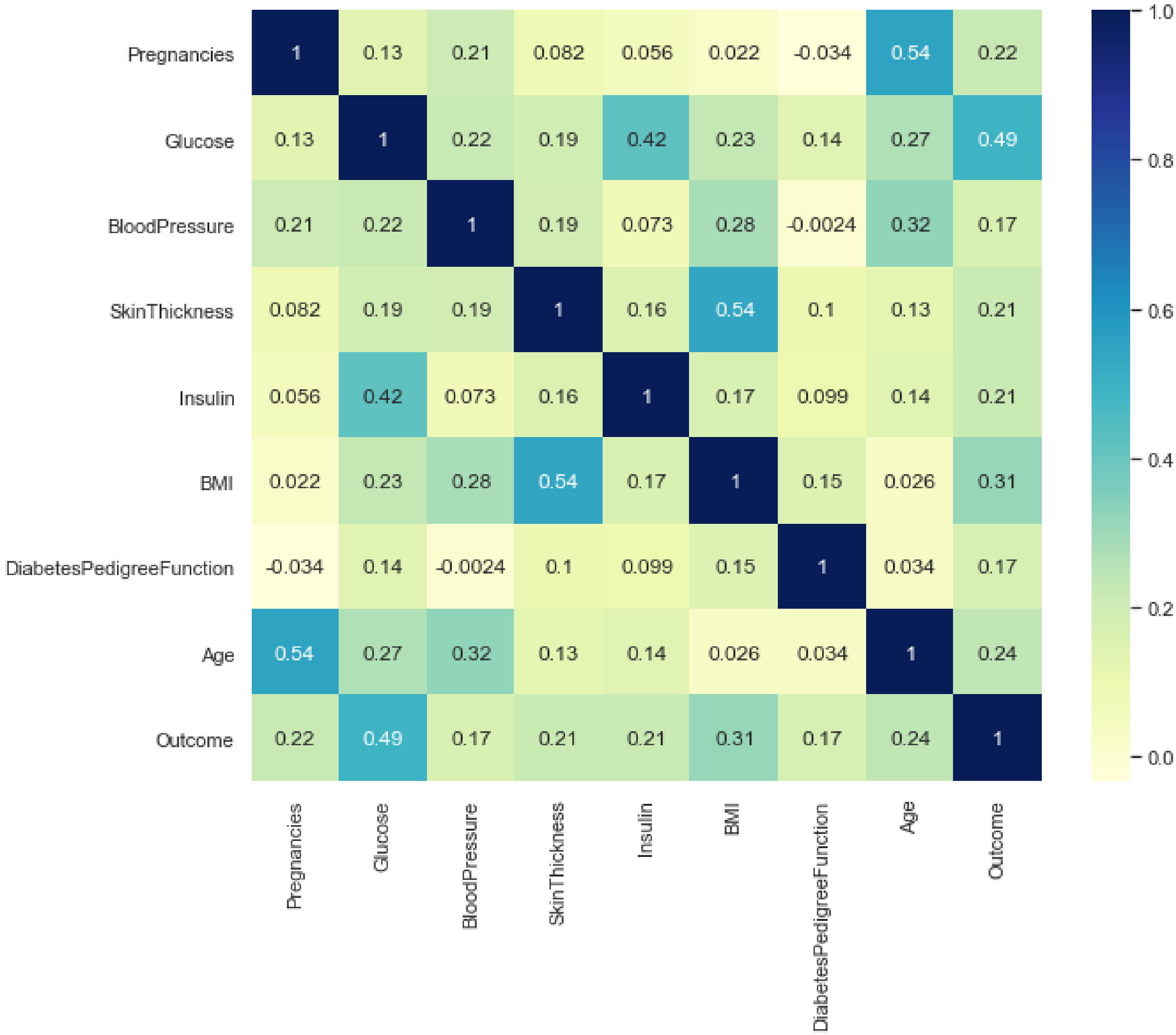
Out[15]:

```
0    500
1    268
Name: Outcome, dtype: int64
```

In [16]:

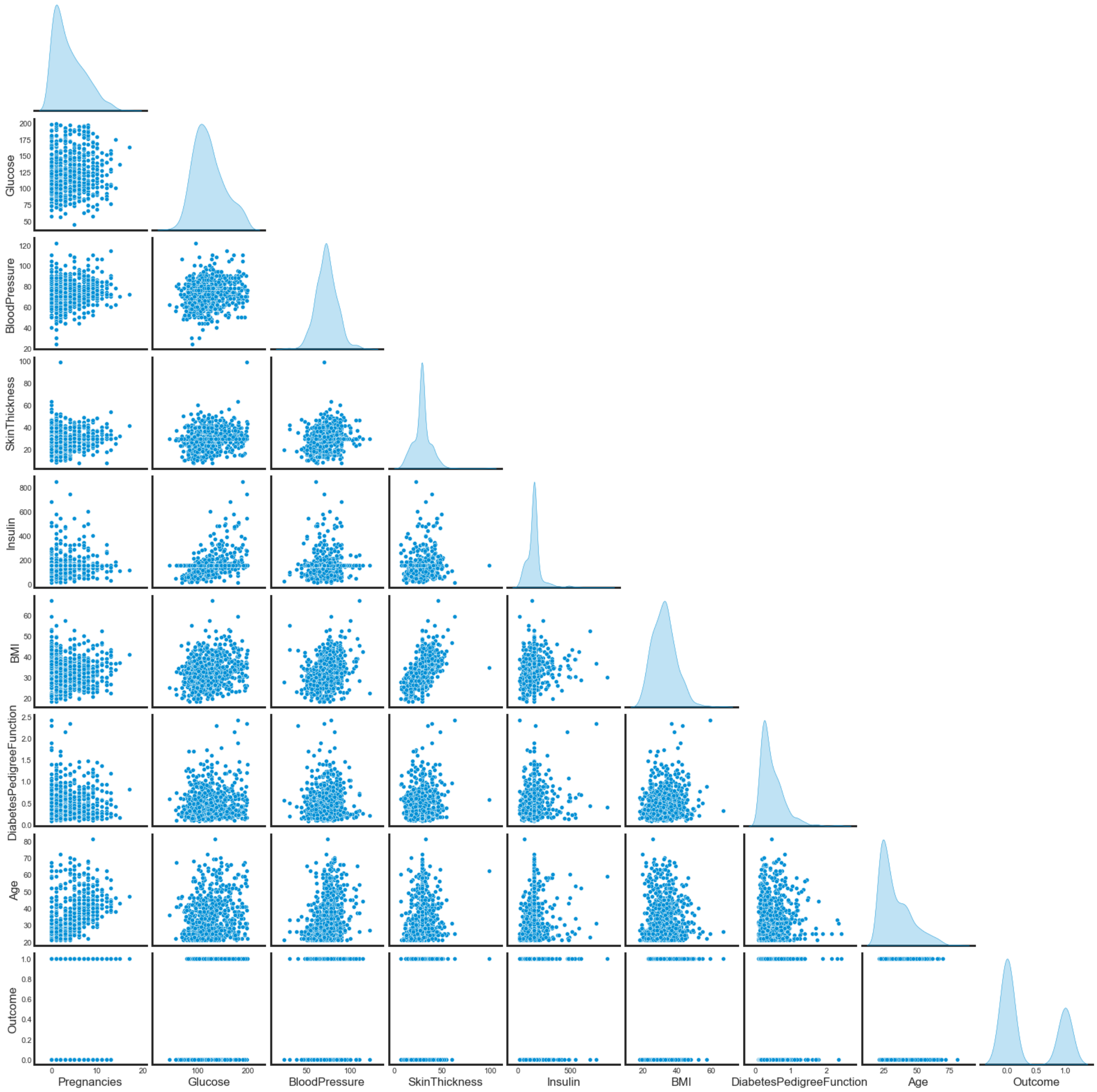
```
sns.heatmap(data=data.corr(), annot=True, cmap="YlGnBu")
```

Out[16]: <AxesSubplot:>



In [28]:
```
plt.style.use('fivethirtyeight')
sns.set_style("white")
sns.pairplot(data=data, diag_kind='kde', corner=True)
```

Out[28]: <seaborn.axisgrid.PairGrid at 0x2b0ad88fa00>



from the above we get some insights

1.BMI and SkinThickness has positive correlation

2.Age and Pregnancies has a relation

3. Insulin and Glucose has somewhat positive correlation

In [60]:
```
#data.to_csv('updated_data.csv')
```

In [19]:
```
X, Y=data.iloc[:,0:8], data.iloc[:, 8]
```

In [20]:
```
smt=SMOTETomek(random_state=43)
X_smt, Y_smt=smt.fit_resample(X, Y)
```

In [21]:

```
Y.value_counts(), Y_smt.value_counts()
```

Out[21]:
```
(0    500
 1    268
 Name: Outcome, dtype: int64,
 0    470
 1    470
 Name: Outcome, dtype: int64)
```

as we can see we balanced our dataset using smotetek

In [35]:
```
x_train, x_test, y_train, y_test=train_test_split(X_smt, Y_smt, test_size=0.3, rando
```

In [37]:
```
st=StandardScaler()
```

In [38]:
```
x_train=st.fit_transform(x_train)
x_test=st.transform(x_test)
```

as the dependent variable is categorical(1 or 0).we go with supervised machine learning algorithms.

we take classification algorithms from supervised learning

In [39]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
```

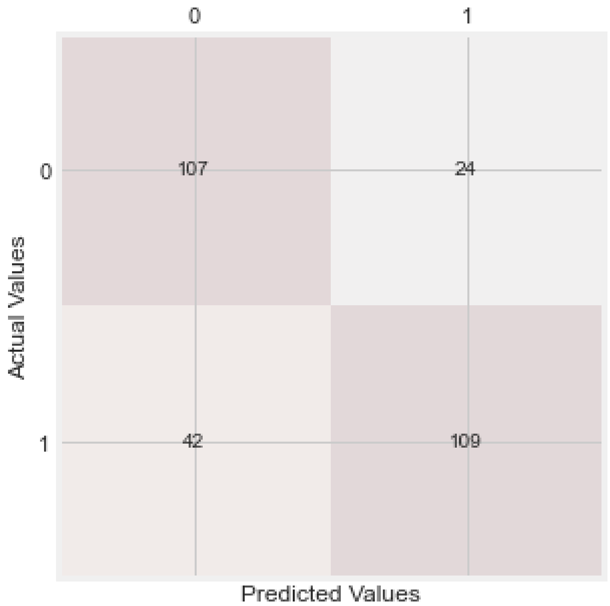
In [40]:
```
lr=LogisticRegression()
dtc=DecisionTreeClassifier()
knn=KNeighborsClassifier()
svc=SVC()
```

In [41]:
```
model_lst=[('Logistic Regression',lr),('Decision Tree',dtc),('KNearestNeighbour',knn
```

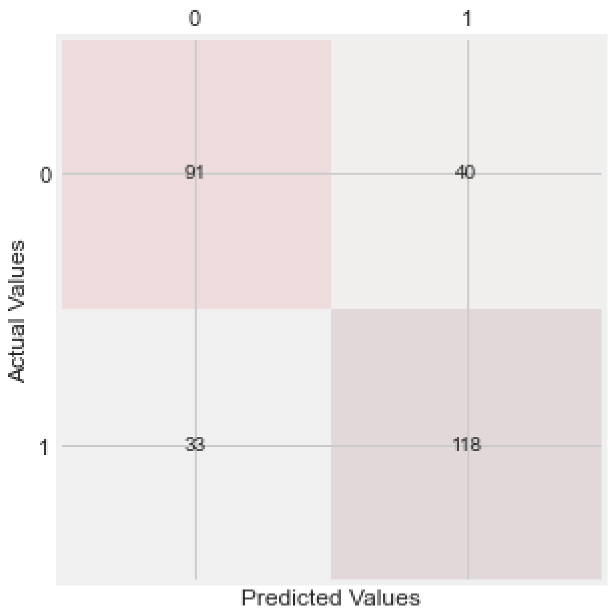
In [43]:
```
import matplotlib.pyplot as plt

from IPython.display import Image, display
%matplotlib inline
for name, model in model_lst:
    model.fit(x_train, y_train)
    y_pred=model.predict(x_test)
    print(name)
    #print(classification_report(y_test, y_pred))
    cm=confusion_matrix(y_test, y_pred)
    fig, ax = plt.subplots(figsize=(5, 5))
    ax.matshow(cm, cmap=plt.cm.Reds, alpha=0.1)
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
```

```
                ax.text(x=j, y=i,
                   s=cm[i, j],
                    va='center', ha='center')
    plt.xlabel('Predicted Values', )
    plt.ylabel('Actual Values')
    plt.show()
    print(classification_report(y_test, y_pred ))
```

```
Logistic Regression
```

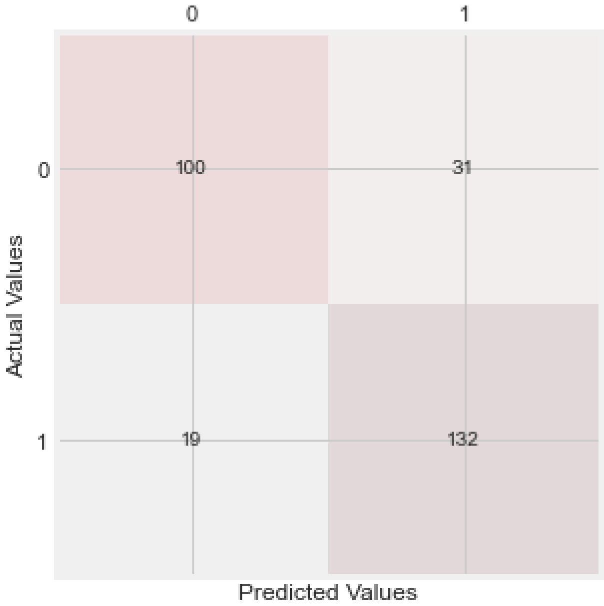



```
              precision    recall  f1-score   support

           0       0.72      0.82      0.76       131
           1       0.82      0.72      0.77       151

    accuracy                           0.77       282
   macro avg       0.77      0.77      0.77       282
weighted avg       0.77      0.77      0.77       282

Decision Tree
```

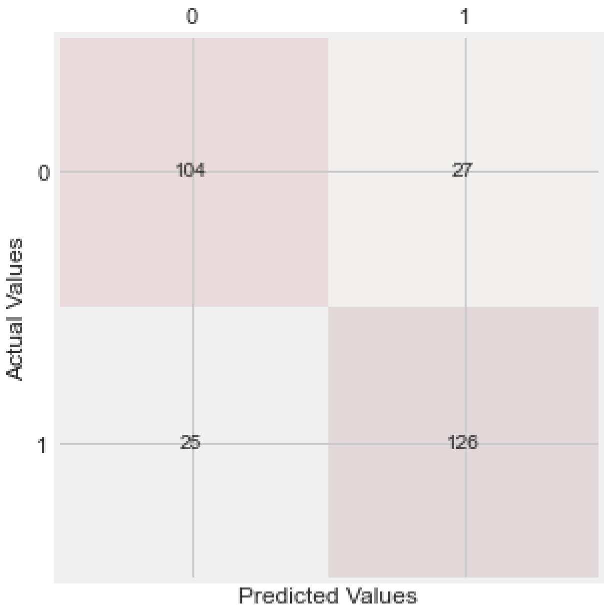



```
              precision    recall  f1-score   support

           0       0.73      0.69      0.71       131
           1       0.75      0.78      0.76       151

    accuracy                           0.74       282
   macro avg       0.74      0.74      0.74       282
```

```
weighted avg       0.74      0.74      0.74       282

KNearestNeighbour
```




```
              precision    recall  f1-score   support

           0       0.84      0.76      0.80       131
           1       0.81      0.87      0.84       151

    accuracy                           0.82       282
   macro avg       0.83      0.82      0.82       282
weighted avg       0.82      0.82      0.82       282

Support Vector Machines
```




```
              precision    recall  f1-score   support

           0       0.81      0.79      0.80       131
           1       0.82      0.83      0.83       151

    accuracy                           0.82       282
   macro avg       0.81      0.81      0.81       282
weighted avg       0.82      0.82      0.82       282
```

In [48]:

```python
X_smt=st.fit_transform(X_smt)
for name, model in model_lst:
    print(name, cross_val_score(model, X_smt, Y_smt, scoring='accuracy', cv=10).mean
```

```
Logistic Regression 0.7659574468085106
Decision Tree 0.747872340425532
KNearestNeighbour 0.7946808510638298
Support Vector Machines 0.801063829787234
```

Hyper Parameter Tuning

we will do tuning for both SVC and KNN

SVC

In [50]:

```
param_grid = {'C': [0.1,1, 10, 100], 'gamma': [1,0.1,0.01,0.001],'kernel': ['rbf', '
grid_svc=GridSearchCV(estimator=SVC(), param_grid=param_grid, cv=10, n_jobs=-1, refi
```

In [51]:

```
grid_svc.fit(x_train, y_train)
```

```
Fitting 10 folds for each of 48 candidates, totalling 480 fits
```

Out[51]:

```
▸ GridSearchCV
▸ estimator: SVC
    ▸ SVC
```

In [53]:

```
print(grid_svc.best_estimator_)
```

```
SVC(C=10, gamma=0.1)
```

In [55]:

```
print("The best parameters are %s with a score of %0.2f"
      % (grid_svc.best_params_, grid_svc.best_score_))
```

```
The best parameters are {'C': 10, 'gamma': 0.1, 'kernel': 'rbf'} with a score of 0.8
1
```

In [60]:

```
grid_svc.best_estimator_.kernel = 'rbf'
hyp_svc=grid_svc.best_estimator_
```

In [61]:

```
print(hyp_svc)
```

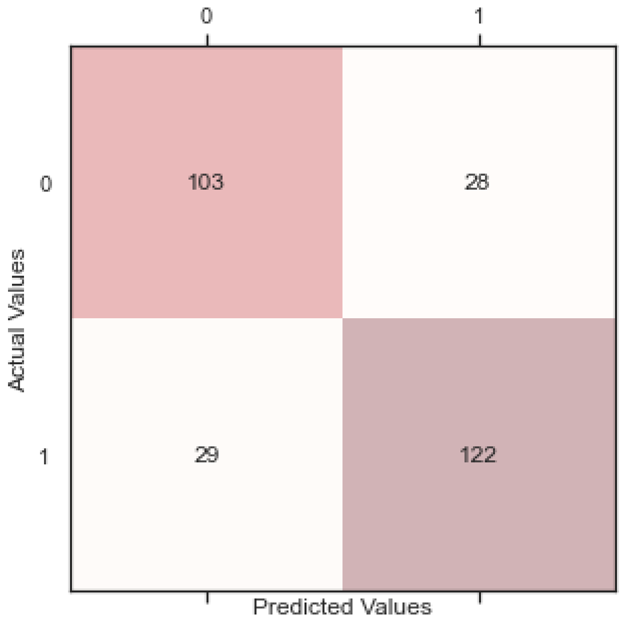
```
SVC(C=10, gamma=0.1, probability=True)
```

In [63]:

```
y_pred = SVC(C=10, gamma=0.1, kernel='rbf').fit(x_train, y_train).predict(x_test)
cm = confusion_matrix(y_test, y_pred)
#print(cm)
print(classification_report(y_test, y_pred ))

fig, ax = plt.subplots(figsize=(5, 5))
ax.matshow(cm, cmap=plt.cm.Reds, alpha=0.3)
for i in range(cm.shape[0]):
     for j in range(cm.shape[1]):
         ax.text(x=j, y=i,
                s=cm[i, j],
                va='center', ha='center')
plt.xlabel('Predicted Values', )
```

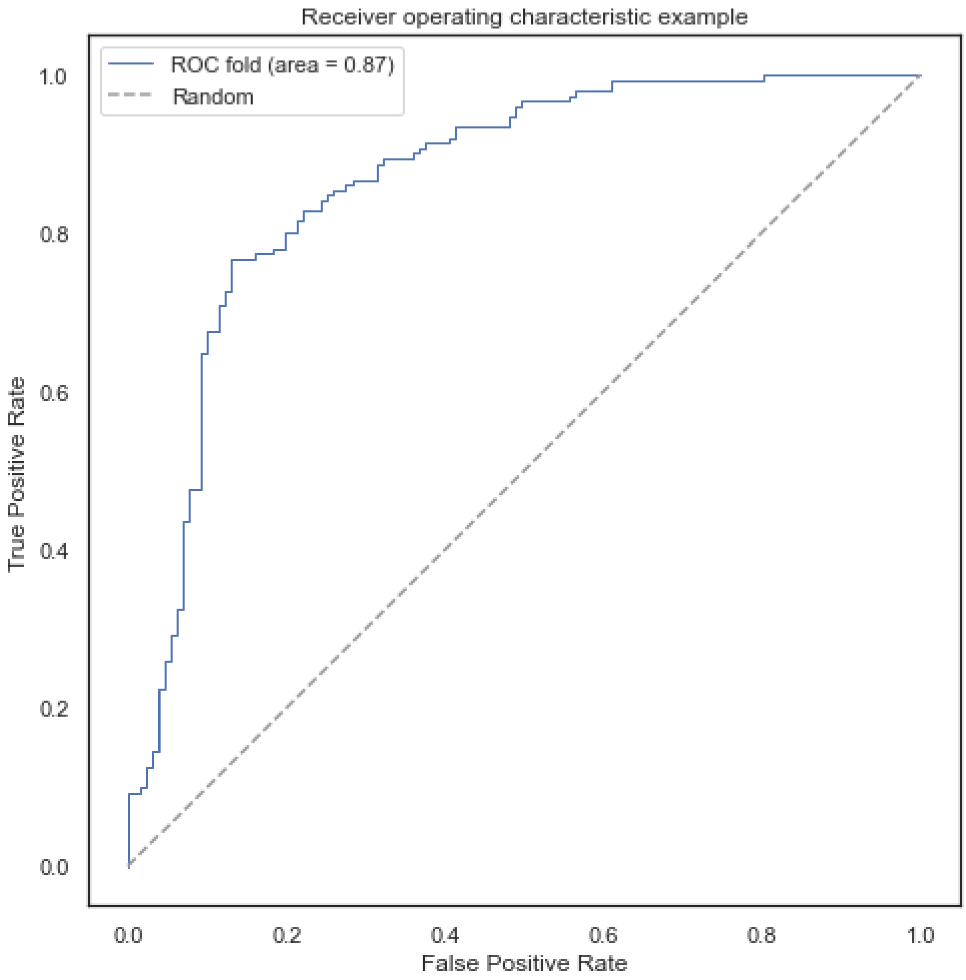
```
plt.ylabel('Actual Values')
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.78      0.79      0.78       131
           1       0.81      0.81      0.81       151

    accuracy                           0.80       282
   macro avg       0.80      0.80      0.80       282
weighted avg       0.80      0.80      0.80       282
```



In [65]:

```
from sklearn.metrics import roc_curve, auc
# Plot the receiver operating characteristic curve (ROC).
plt.figure(figsize=(10,8))
probas_ =hyp_svc.predict_proba(x_test)
fpr, tpr, thresholds = roc_curve(y_test, probas_[:, 1])
roc_auc = auc(fpr, tpr)
plt.plot(fpr, tpr, lw=1, label='ROC fold (area = %0.2f)' % (roc_auc))
plt.plot([0, 1], [0, 1], '--', color=(0.6, 0.6, 0.6), label='Random')
plt.xlim([-0.05, 1.05])
plt.ylim([-0.05, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend()
plt.axes().set_aspect(1)
```



KNN

In [66]:
```
param_grid = { 'n_neighbors' : [5,7,9,11,13,15],
              'leaf_size' : list(range(1,40)),
               'weights' : ['uniform','distance'],
               'metric' : ['minkowski','euclidean','manhattan']}
```

In [67]:
```
grid_knn=GridSearchCV(estimator=KNeighborsClassifier(), param_grid=param_grid, cv=10
```

In [69]:
```
grid_knn.fit(x_train,y_train)
```

```
Fitting 10 folds for each of 1404 candidates, totalling 14040 fits
```

Out[69]:
```
▸ GridSearchCV
▸ estimator: KNeighborsClassifier
    ▸ KNeighborsClassifier
```

In [70]:
```
print(grid_knn.best_estimator_)
```

```
KNeighborsClassifier(leaf_size=1, metric='manhattan', n_neighbors=9,
                     weights='distance')
```

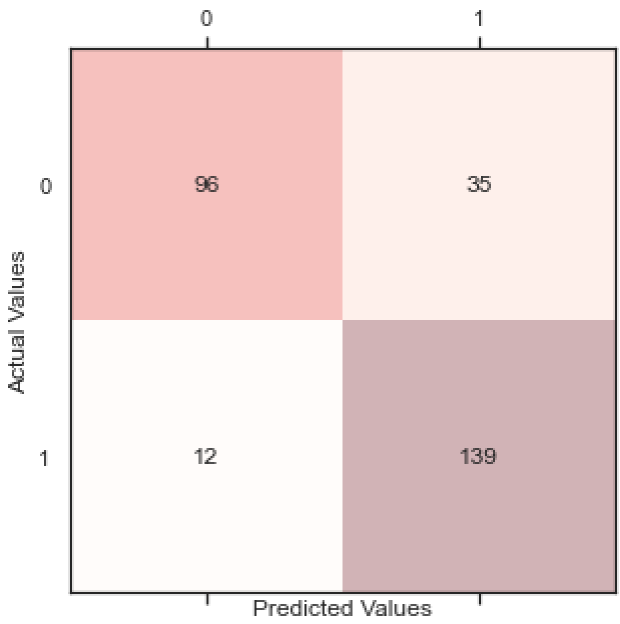
In [72]:
```
print("The best parameters are %s with a score of %0.2f"
      % (grid_knn.best_params_, grid_knn.best_score_))
```

```
The best parameters are {'leaf_size': 1, 'metric': 'manhattan', 'n_neighbors': 9, 'w
eights': 'distance'} with a score of 0.80
```

In [73]:
```
hyp_knn=grid_knn.best_estimator_
```

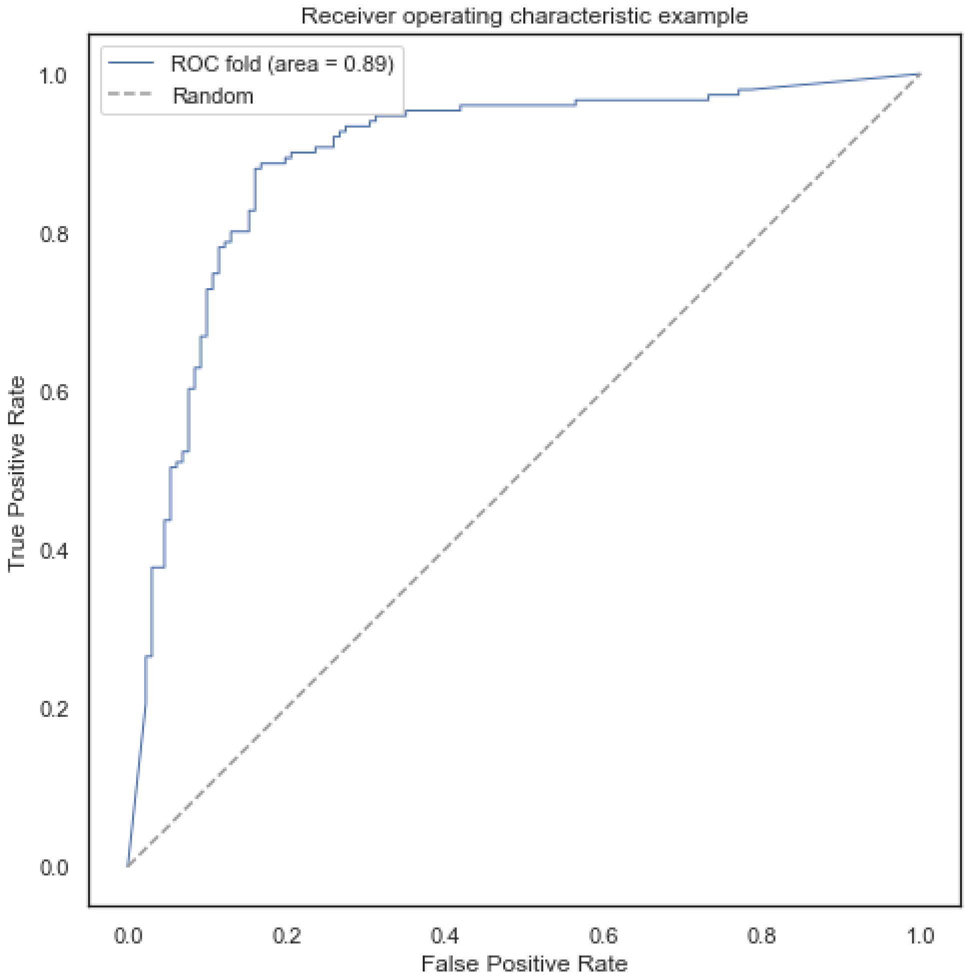
In [74]:
```
y_pred=hyp_knn.fit(x_train, y_train).predict(x_test)
cm = confusion_matrix(y_test, y_pred)
#print(cm)
print(classification_report(y_test, y_pred ))

fig, ax = plt.subplots(figsize=(5, 5))
ax.matshow(cm, cmap=plt.cm.Reds, alpha=0.3)
for i in range(cm.shape[0]):
     for j in range(cm.shape[1]):
         ax.text(x=j, y=i,
                s=cm[i, j],
                va='center', ha='center')
plt.xlabel('Predicted Values', )
plt.ylabel('Actual Values')
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.89      0.73      0.80       131
           1       0.80      0.92      0.86       151

    accuracy                           0.83       282
   macro avg       0.84      0.83      0.83       282
weighted avg       0.84      0.83      0.83       282
```



In [75]:
```
from sklearn.metrics import roc_curve, auc
# Plot the receiver operating characteristic curve (ROC).
plt.figure(figsize=(10,8))
probas_ =hyp_knn.predict_proba(x_test)
fpr, tpr, thresholds = roc_curve(y_test, probas_[:, 1])
roc_auc = auc(fpr, tpr)
plt.plot(fpr, tpr, lw=1, label='ROC fold (area = %0.2f)' % (roc_auc))
plt.plot([0, 1], [0, 1], '--', color=(0.6, 0.6, 0.6), label='Random')
plt.xlim([-0.05, 1.05])
plt.ylim([-0.05, 1.05])
plt.xlabel('False Positive Rate')
```

```
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend()
plt.axes().set_aspect(1)
```



After Hyper Parameter Tuning its showing that KNN is slightly good than SVC

In [ ]: