In [2]:
```
# Load libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from scipy.stats import ttest_ind

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn import metrics
```

In [3]:
```
# Load dataset
diabetes_data_binary = pd.read_csv('diabetes_data_upload.csv')
diabetes_data_floats = pd.read_csv('diabetes-dataset.csv')
```

In [4]:
```
# Display original binary dataset
print(diabetes_data_binary.info())
diabetes_data_binary.head(10)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 520 entries, 0 to 519
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Age                 520 non-null    int64 
 1   Gender              520 non-null    object
 2   Polyuria            520 non-null    object
 3   Polydipsia          520 non-null    object
 4   sudden weight loss  520 non-null    object
 5   weakness            520 non-null    object
 6   Polyphagia          520 non-null    object
 7   Genital thrush      520 non-null    object
 8   visual blurring     520 non-null    object
 9   Itching             520 non-null    object
 10  Irritability        520 non-null    object
 11  delayed healing     520 non-null    object
 12  partial paresis     520 non-null    object
 13  muscle stiffness    520 non-null    object
 14  Alopecia            520 non-null    object
 15  Obesity             520 non-null    object
 16  class               520 non-null    object
dtypes: int64(1), object(16)
memory usage: 69.2+ KB
None
```

Out[4]:

	Age	Gender	Polyuria	Polydipsia	sudden weight loss	weakness	Polyphagia	Genital thrush	visual blurring	Itching
0	40	Male	No	Yes	No	Yes	No	No	No	Yes
1	58	Male	No	No	No	Yes	No	No	Yes	No
2	41	Male	Yes	No	No	Yes	Yes	No	No	Yes
3	45	Male	No	No	Yes	Yes	Yes	Yes	No	Yes
4	60	Male	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
5	55	Male	Yes	Yes	No	Yes	Yes	No	Yes	Yes
6	57	Male	Yes	Yes	No	Yes	Yes	Yes	No	No
7	66	Male	Yes	Yes	Yes	Yes	No	No	Yes	Yes
8	67	Male	Yes	Yes	No	Yes	Yes	Yes	No	Yes
9	70	Male	No	Yes	Yes	Yes	Yes	No	Yes	Yes

In [ ]:

In [5]:
```
# Map string values to int for the binary dataset

# Convert Yes/No values to 1/0 values
diabetes_data_binary = diabetes_data_binary.applymap(lambda x: 1 if x=='Yes' e
lse x)
diabetes_data_binary = diabetes_data_binary.applymap(lambda x: 0 if x=='No' el
se x)

# Convert Pos/Neg values to 1/0 values
diabetes_data_binary = diabetes_data_binary.applymap(lambda x: 1 if x=='Positi
ve' else x)
diabetes_data_binary = diabetes_data_binary.applymap(lambda x: 0 if x=='Negati
ve' else x)

# Rename Gender column to Male
diabetes_data_binary = diabetes_data_binary.rename(columns={'Gender': 'Male'})

# Convert Male/Female values to 1/0 values
diabetes_data_binary['Male'] = diabetes_data_binary['Male'].map({'Male': 1, 'F
emale': 0})
```

In [ ]:
```
```

In [6]:
```
# Display binary dataset after data preparation
print(diabetes_data_binary.info())
diabetes_data_binary
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 520 entries, 0 to 519
Data columns (total 17 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Age                  520 non-null    int64
 1   Male                 520 non-null    int64
 2   Polyuria             520 non-null    int64
 3   Polydipsia           520 non-null    int64
 4   sudden weight loss   520 non-null    int64
 5   weakness             520 non-null    int64
 6   Polyphagia           520 non-null    int64
 7   Genital thrush       520 non-null    int64
 8   visual blurring      520 non-null    int64
 9   Itching              520 non-null    int64
 10  Irritability         520 non-null    int64
 11  delayed healing      520 non-null    int64
 12  partial paresis      520 non-null    int64
 13  muscle stiffness     520 non-null    int64
 14  Alopecia             520 non-null    int64
 15  Obesity              520 non-null    int64
 16  class                520 non-null    int64
dtypes: int64(17)
memory usage: 69.2 KB
None
```

Out[6]:

	Age	Male	Polyuria	Polydipsia	sudden weight loss	weakness	Polyphagia	Genital thrush	visual blurring	Itching
0	40	1	0	1	0	1	0	0	0	1
1	58	1	0	0	0	1	0	0	1	0
2	41	1	1	0	0	1	1	0	0	1
3	45	1	0	0	1	1	1	1	0	1
4	60	1	1	1	1	1	1	0	1	1
...	...	...	...	...	...	...	...	...	...	...
515	39	0	1	1	1	0	1	0	0	1
516	48	0	1	1	1	1	1	0	0	1
517	58	0	1	1	1	1	1	0	1	0
518	32	0	0	0	0	1	0	0	1	1
519	42	1	0	0	0	0	0	0	0	0

520 rows × 17 columns

In [ ]:

In [ ]:

In [7]:
```
# Display original integer/float dataset
print(diabetes_data_floats.info())
diabetes_data_floats.head(10)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               2000 non-null   int64  
 1   Glucose                   2000 non-null   int64  
 2   BloodPressure             2000 non-null   int64  
 3   SkinThickness             2000 non-null   int64  
 4   Insulin                   2000 non-null   int64  
 5   BMI                       2000 non-null   float64
 6   DiabetesPedigreeFunction  2000 non-null   float64
 7   Age                       2000 non-null   int64  
 8   Outcome                   2000 non-null   int64  
dtypes: float64(2), int64(7)
memory usage: 140.8 KB
None
```

Out[7]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction
0	2	138	62	35	0	33.6	0.127
1	0	84	82	31	125	38.2	0.233
2	0	145	0	0	0	44.2	0.630
3	0	135	68	42	250	42.3	0.365
4	1	139	62	41	480	40.7	0.536
5	0	173	78	32	265	46.5	1.159
6	4	99	72	17	0	25.6	0.294
7	8	194	80	0	0	26.1	0.551
8	2	83	65	28	66	36.8	0.629
9	2	89	90	30	0	33.5	0.292

In [ ]:

In [8]:
```
# Count missing values for integers/floats dataset
```

In [9]:
```
diabetes_data_floats[diabetes_data_floats['Glucose']==0].shape[0]
```

Out[9]: 13

In [10]:
```
diabetes_data_floats[diabetes_data_floats['BloodPressure']==0].shape[0]
```

Out[10]: 90

In [11]:
```
diabetes_data_floats[diabetes_data_floats['SkinThickness']==0].shape[0]
```

Out[11]: 573

In [12]:
```
diabetes_data_floats[diabetes_data_floats['Insulin']==0].shape[0]
```

Out[12]: 956

In [13]:
```
diabetes_data_floats[diabetes_data_floats['BMI']==0].size
```

Out[13]: 252

In [ ]:

In [14]:
```
# Remove all observations with missing values
diabetes_data_floats = diabetes_data_floats[diabetes_data_floats['Glucose']!=0
]
diabetes_data_floats = diabetes_data_floats[diabetes_data_floats['BloodPressur
e']!=0]
diabetes_data_floats = diabetes_data_floats[diabetes_data_floats['SkinThicknes
s']!=0]
diabetes_data_floats = diabetes_data_floats[diabetes_data_floats['Insulin']!=0
]
diabetes_data_floats = diabetes_data_floats[diabetes_data_floats['BMI']!=0]
```

In [ ]:

In [15]:
```
# Display integer/float dataset after data cleaning
print(diabetes_data_floats.info())
diabetes_data_floats.head(10)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1035 entries, 1 to 1999
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               1035 non-null   int64  
 1   Glucose                   1035 non-null   int64  
 2   BloodPressure             1035 non-null   int64  
 3   SkinThickness             1035 non-null   int64  
 4   Insulin                   1035 non-null   int64  
 5   BMI                       1035 non-null   float64
 6   DiabetesPedigreeFunction  1035 non-null   float64
 7   Age                       1035 non-null   int64  
 8   Outcome                   1035 non-null   int64  
dtypes: float64(2), int64(7)
memory usage: 80.9 KB
None
```

Out[15]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctio
1	0	84	82	31	125	38.2	0.23
3	0	135	68	42	250	42.3	0.36
4	1	139	62	41	480	40.7	0.53
5	0	173	78	32	265	46.5	1.15
8	2	83	65	28	66	36.8	0.62
11	4	125	70	18	122	28.9	1.14
15	2	81	72	15	76	30.1	0.54
16	7	195	70	33	145	25.1	0.16
17	6	154	74	32	193	29.3	0.83
18	2	117	90	19	71	25.2	0.31

In [ ]:

In [ ]:

In [16]:
```
# Computing averages for diabetic and non-diabetic patients using integer/floa
ts dataset
```

In [17]:
```
print("Pregnancies")
print("Non-Diabetic Mean:", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['Pregnancies'].mean())
print("Diabetic Mean    :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['Pregnancies'].mean())
print()
print("Non-Diabetic std :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['Pregnancies'].std())
print("Diabetic std     :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['Pregnancies'].std())
print()
ttest_ind(diabetes_data_floats[diabetes_data_floats['Outcome']==1]['Pregnancie
s'], diabetes_data_floats[diabetes_data_floats['Outcome']==0]['Pregnancies'],
equal_var=False)
```

```
Pregnancies
Non-Diabetic Mean: 2.603151862464183
Diabetic Mean    : 4.3916913946587535

Non-Diabetic std : 2.5541686931203627
Diabetic std     : 3.8960819512872114
```

Out[17]:
```
Ttest_indResult(statistic=7.669055764939621, pvalue=9.717868756815654e-14)
```

In [ ]:

In [18]:
```
print("Glucose")
print("Non-Diabetic Mean:", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['Glucose'].mean())
print("Diabetic Mean    :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['Glucose'].mean())
print()
print("Non-Diabetic std :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['Glucose'].std())
print("Diabetic std     :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['Glucose'].std())
print()
ttest_ind(diabetes_data_floats[diabetes_data_floats['Outcome']==1]['Glucose'],
diabetes_data_floats[diabetes_data_floats['Outcome']==0]['Glucose'], equal_var
=False)
```

```
Glucose
Non-Diabetic Mean: 111.7378223495702
Diabetic Mean    : 145.84272997032642

Non-Diabetic std : 24.606662425248683
Diabetic std     : 29.136106337756964
```

Out[18]:
```
Ttest_indResult(statistic=18.53284052946368, pvalue=1.862453776362188e-60)
```

In [ ]:

In [19]:
```
print("BloodPressure ")
print("Non-Diabetic Mean:", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['BloodPressure'].mean())
print("Diabetic Mean    :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['BloodPressure'].mean())
print()
print("Non-Diabetic std :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['BloodPressure'].std())
print("Diabetic std     :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['BloodPressure'].std())
print()
ttest_ind(diabetes_data_floats[diabetes_data_floats['Outcome']==1]['BloodPress
ure'], diabetes_data_floats[diabetes_data_floats['Outcome']==0]['BloodPressur
e'], equal_var=False)
```

```
BloodPressure
Non-Diabetic Mean: 68.98424068767908
Diabetic Mean    : 74.5727002967359

Non-Diabetic std : 11.7922491534455
Diabetic std     : 12.599422327405149
```

Out[19]:
```
Ttest_indResult(statistic=6.825979203640128, pvalue=2.0666122575138323e-11)
```

In [ ]:

In [20]:
```
print("SkinThickness ")
print("Non-Diabetic Mean:", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['SkinThickness'].mean())
print("Diabetic Mean    :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['SkinThickness'].mean())
print()
print("Non-Diabetic std :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['SkinThickness'].std())
print("Diabetic std     :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['SkinThickness'].std())
print()
ttest_ind(diabetes_data_floats[diabetes_data_floats['Outcome']==1]['SkinThickn
ess'], diabetes_data_floats[diabetes_data_floats['Outcome']==0]['SkinThicknes
s'], equal_var=False)
```

```
SkinThickness
Non-Diabetic Mean: 27.302292263610315
Diabetic Mean    : 33.32640949554896

Non-Diabetic std : 10.291672911794015
Diabetic std     : 9.941809106994036
```

Out[20]:
```
Ttest_indResult(statistic=9.0301455996166, pvalue=1.7188263087543889e-18)
```

In [ ]:

In [21]:
```
print("Insulin ")
print("Non-Diabetic Mean:", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['Insulin'].mean())
print("Diabetic Mean    :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['Insulin'].mean())
print()
print("Non-Diabetic std :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['Insulin'].std())
print("Diabetic std     :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['Insulin'].std())
print()
ttest_ind(diabetes_data_floats[diabetes_data_floats['Outcome']==1]['Insulin'],
diabetes_data_floats[diabetes_data_floats['Outcome']==0]['Insulin'], equal_var
=False)
```

```
Insulin
Non-Diabetic Mean: 131.3595988538682
Diabetic Mean    : 200.7299703264095

Non-Diabetic std : 99.73279034570396
Diabetic std     : 119.84536697766426
```

Out[21]:
```
Ttest_indResult(statistic=9.198817762526524, pvalue=6.848789084574853e-19)
```

In [ ]:

In [22]:
```
print("BMI ")
print("Non-Diabetic Mean:", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['BMI'].mean())
print("Diabetic Mean    :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['BMI'].mean())
print()
print("Non-Diabetic std :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['BMI'].std())
print("Diabetic std     :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['BMI'].std())
print()
ttest_ind(diabetes_data_floats[diabetes_data_floats['Outcome']==1]['BMI'], dia
betes_data_floats[diabetes_data_floats['Outcome']==0]['BMI'], equal_var=False)
```

```
BMI
Non-Diabetic Mean: 32.08939828080229
Diabetic Mean    : 35.83086053412463

Non-Diabetic std : 6.847662059242316
Diabetic std     : 6.949854197349751
```

Out[22]:
```
Ttest_indResult(statistic=8.154776053796434, pvalue=1.7833653506931635e-15)
```

In [ ]:

In [23]:
```
print("Diabetes Pedigree Function")
print("Non-Diabetic Mean:", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['DiabetesPedigreeFunction'].mean())
print("Diabetic Mean    :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['DiabetesPedigreeFunction'].mean())
print()
print("Non-Diabetic std :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==0]['DiabetesPedigreeFunction'].std())
print("Diabetic std     :", diabetes_data_floats[diabetes_data_floats['Outcom
e']==1]['DiabetesPedigreeFunction'].std())
print()
ttest_ind(diabetes_data_floats[diabetes_data_floats['Outcome']==1]['DiabetesPe
digreeFunction'], diabetes_data_floats[diabetes_data_floats['Outcome']==0]['Di
abetesPedigreeFunction'], equal_var=False)
```

```
Diabetes Pedigree Function
Non-Diabetic Mean: 0.47991977077363895
Diabetic Mean    : 0.6117329376854599

Non-Diabetic std : 0.2939575738895091
Diabetic std     : 0.38573929468677604
```

Out[23]:
```
Ttest_indResult(statistic=5.543824040855261, pvalue=4.670348451789813e-08)
```

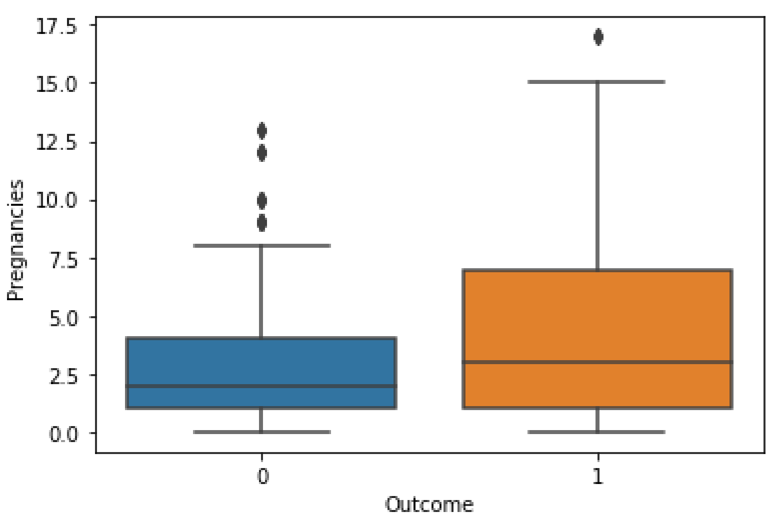
In [ ]:

In [ ]:

In [24]:
```
# Visualize feature statistics for non-diabetic and diabetic patients using in
teger/floats dataset
```

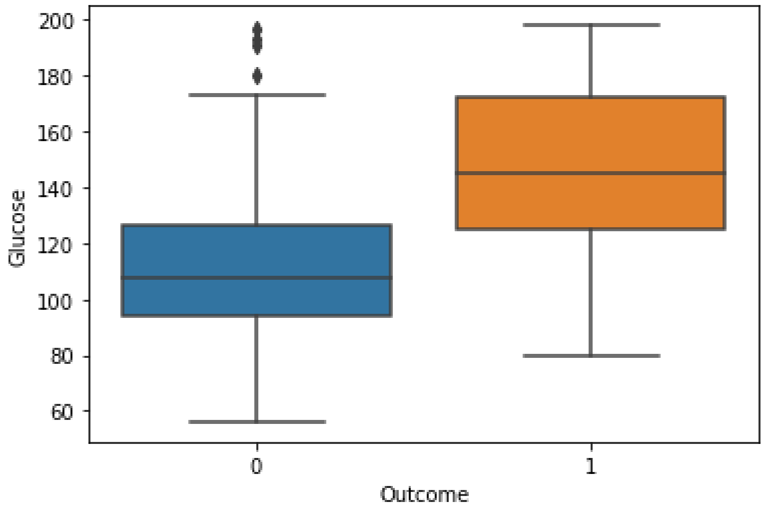
In [25]:
```
sns.boxplot(x='Outcome',y='Pregnancies',data=diabetes_data_floats)
```

Out[25]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x21788ff5188>
```



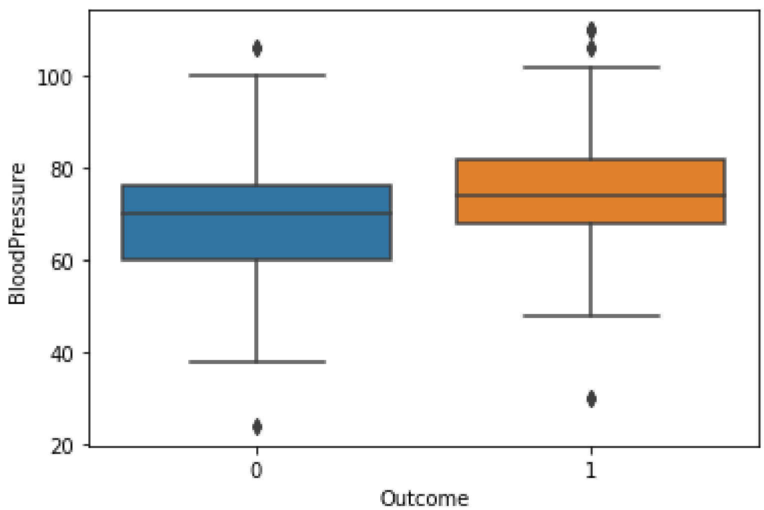
In [26]:
```
sns.boxplot(x='Outcome',y='Glucose',data=diabetes_data_floats)
```

Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x21788ef1848>



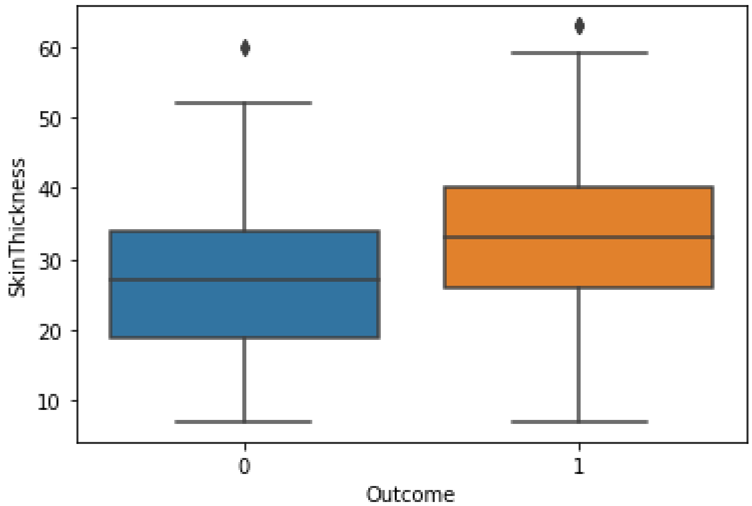
In [27]:
```
sns.boxplot(x='Outcome',y='BloodPressure',data=diabetes_data_floats)
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b156a48>



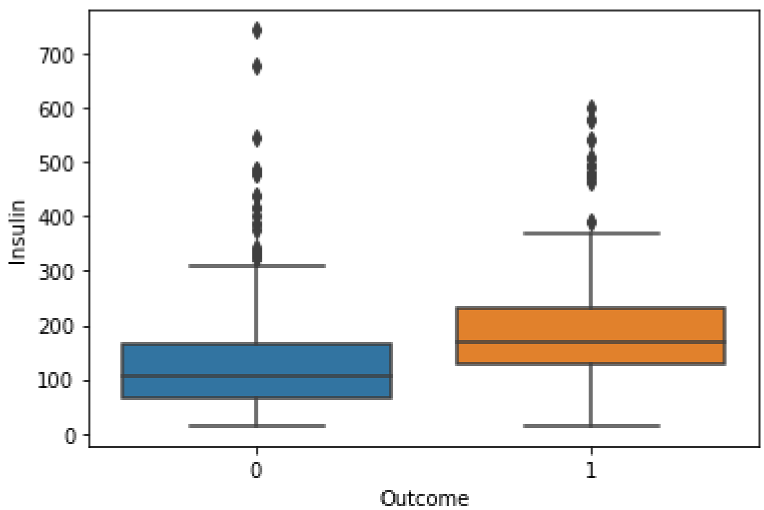
In [28]:
```
sns.boxplot(x='Outcome',y='SkinThickness',data=diabetes_data_floats)
```

Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b0e0308>



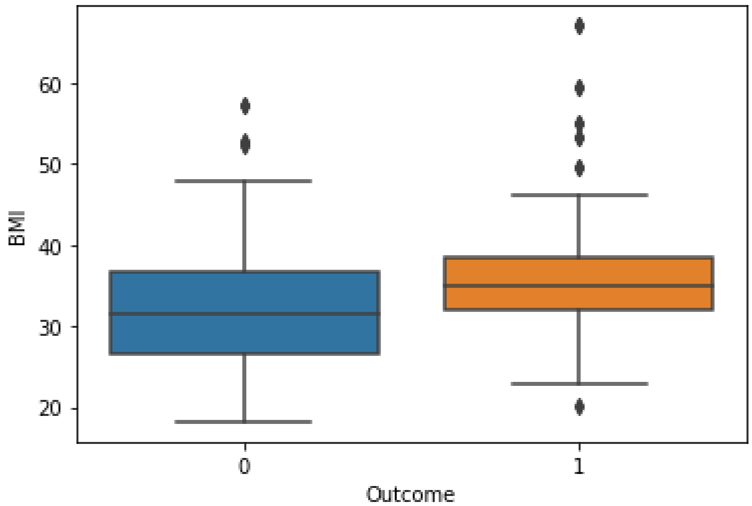
In [29]:
```
sns.boxplot(x='Outcome',y='Insulin',data=diabetes_data_floats)
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b27e788>



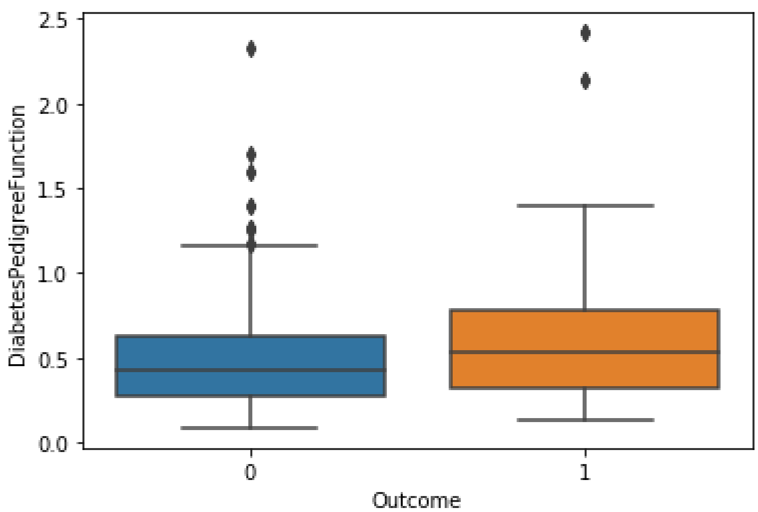
In [30]:
```
sns.boxplot(x='Outcome',y='BMI',data=diabetes_data_floats)
```

Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b30b988>



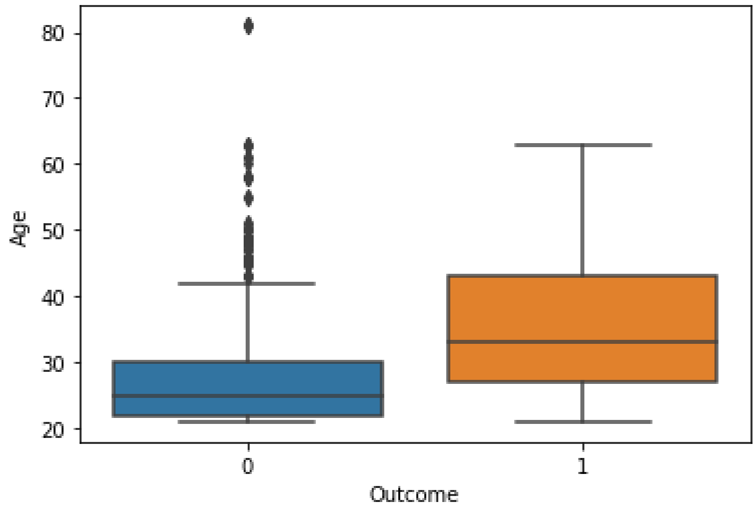
In [31]:
```
sns.boxplot(x='Outcome',y='DiabetesPedigreeFunction',data=diabetes_data_floats
)
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b381908>



In [32]:
```
sns.boxplot(x='Outcome',y='Age',data=diabetes_data_floats)
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b402a88>



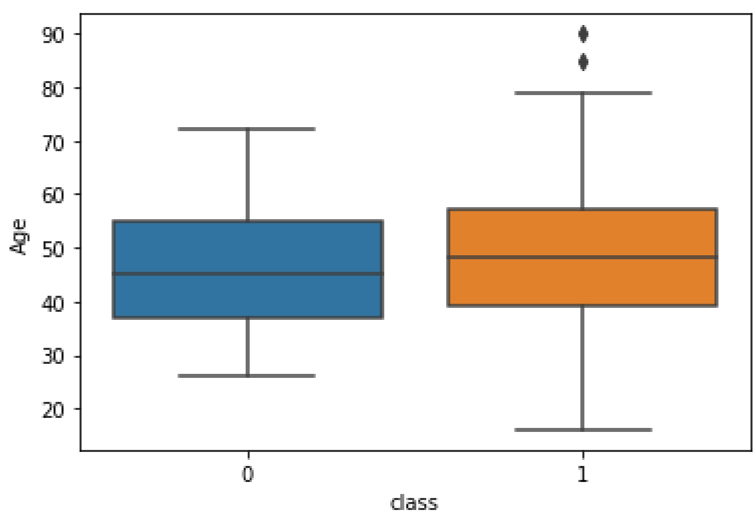
In [33]:
```
#Most relevant variables seem to be glucose,age,insulin,and skin thickness
```

In [ ]:

In [34]:
```
# Visualize feature statistics for non-diabetic and diabetic patients using bi
nary dataset
```

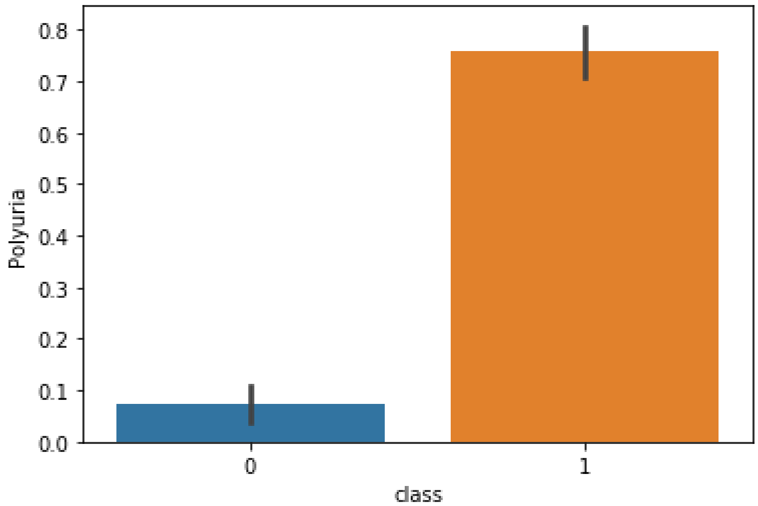
In [35]:
```
sns.boxplot(x='class',y='Age',data=diabetes_data_binary)
```

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b477208>



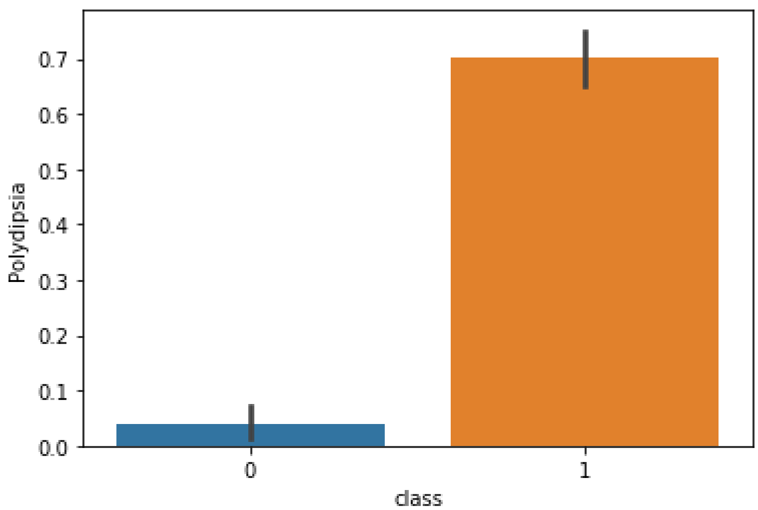
In [36]:
```
sns.barplot(x='class',y='Polyuria',data=diabetes_data_binary)
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b4f8648>



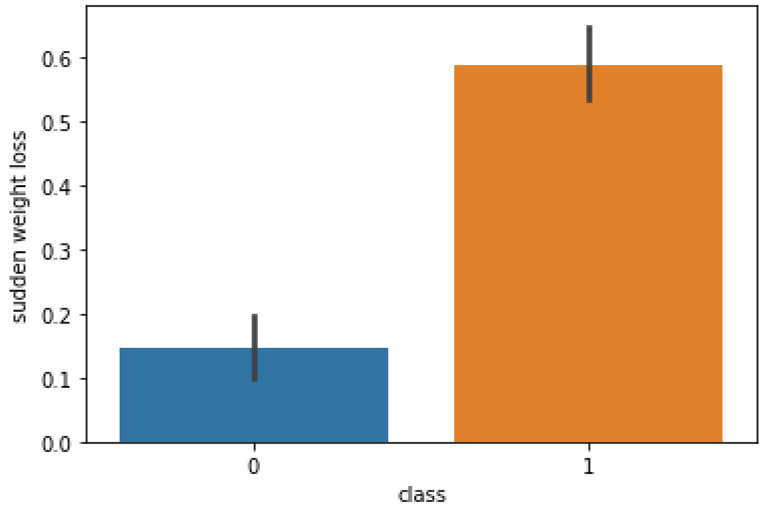
In [37]:
```
sns.barplot(x='class',y='Polydipsia',data=diabetes_data_binary)
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b56c988>



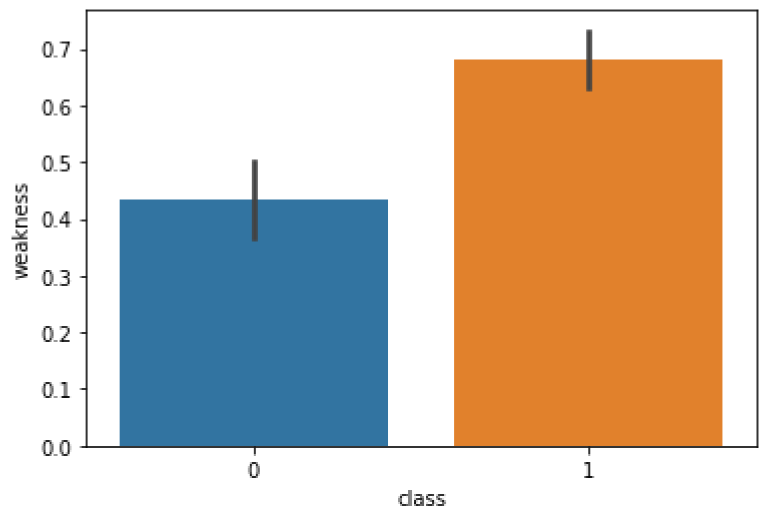
In [38]:
```
sns.barplot(x='class',y='sudden weight loss',data=diabetes_data_binary)
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b5c47c8>



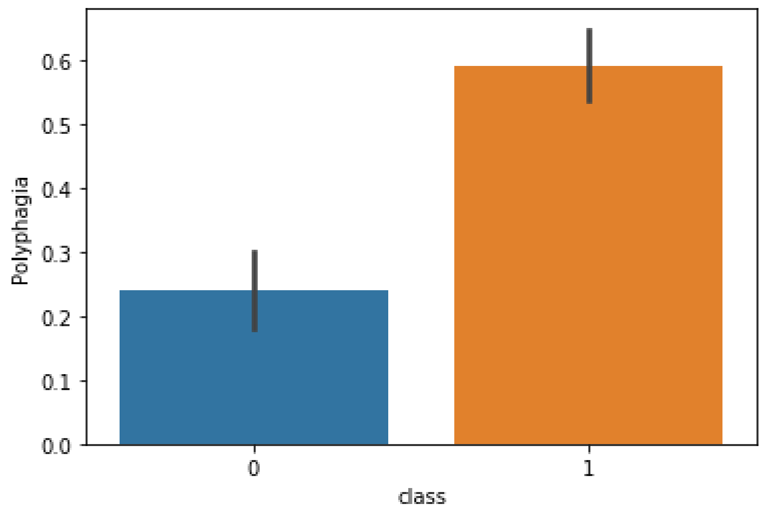
In [39]:
```
sns.barplot(x='class',y='weakness',data=diabetes_data_binary)
```

Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b629948>



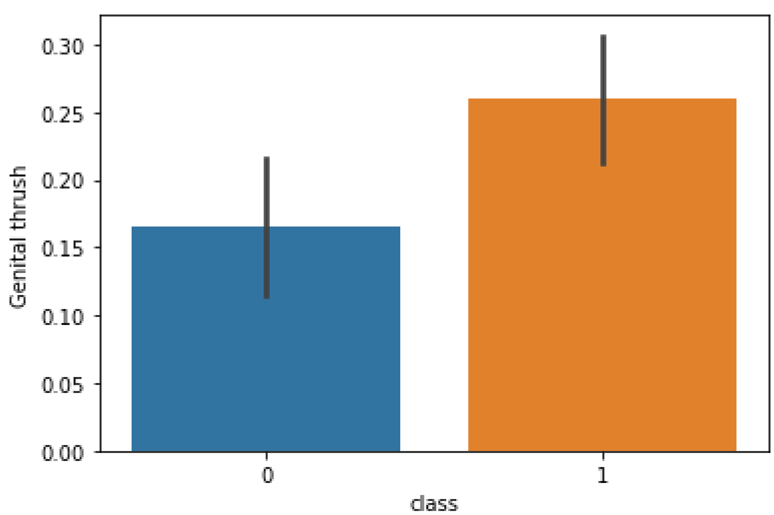
In [40]:
```
sns.barplot(x='class',y='Polyphagia',data=diabetes_data_binary)
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b6909c8>



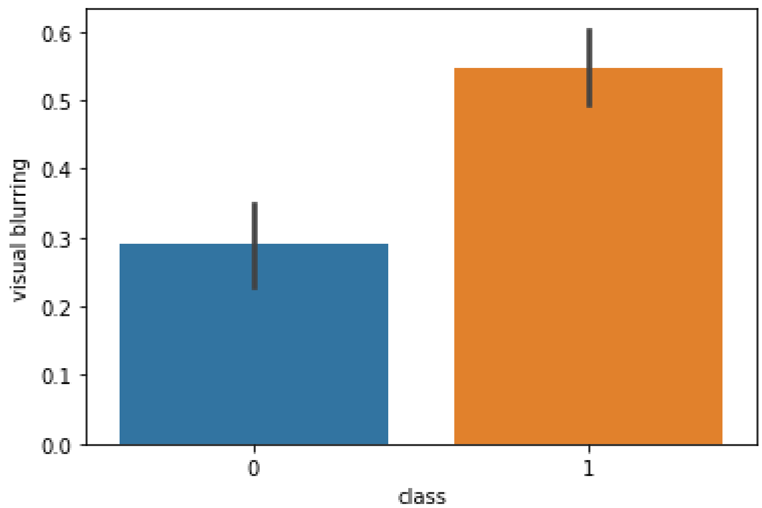
In [41]:
```
sns.barplot(x='class',y='Genital thrush',data=diabetes_data_binary)
```

Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b6ea688>



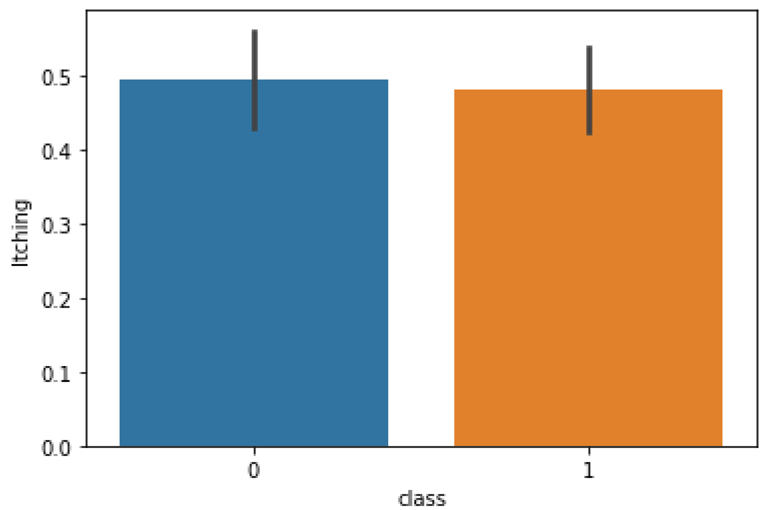
In [42]:
```
sns.barplot(x='class',y='visual blurring',data=diabetes_data_binary)
```

Out[42]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b755048>



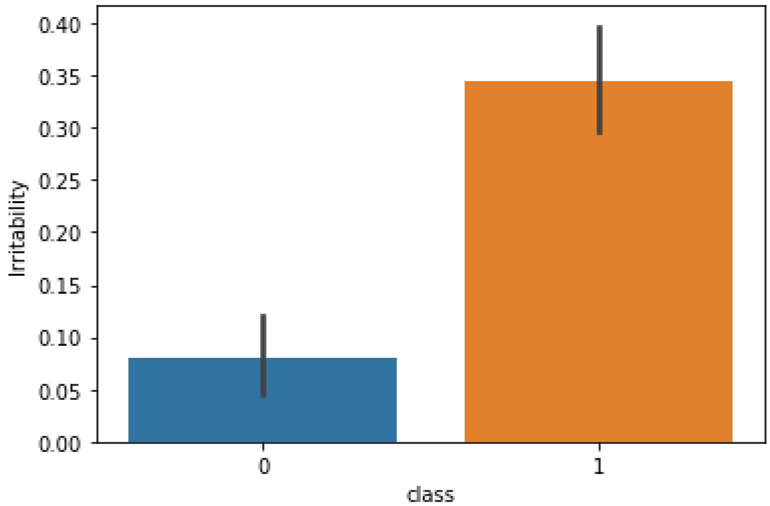
In [43]:
```
sns.barplot(x='class',y='Itching',data=diabetes_data_binary)
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b6e64c8>



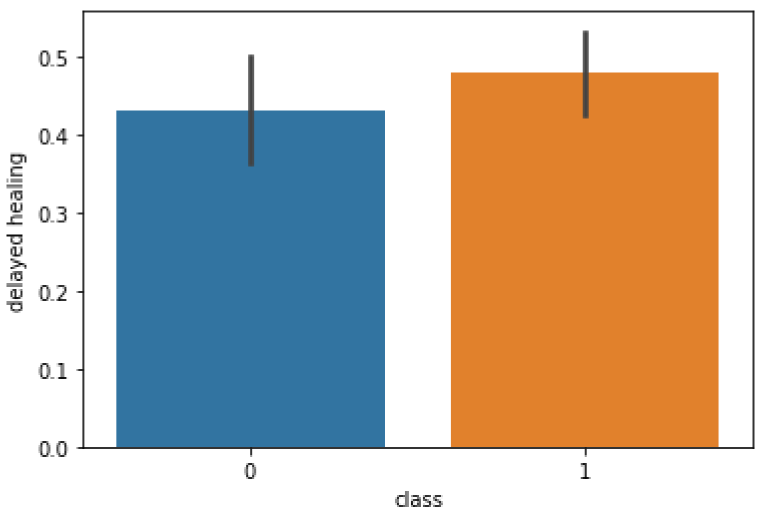
In [44]:
```
sns.barplot(x='class',y='Irritability',data=diabetes_data_binary)
```

Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b80ee08>



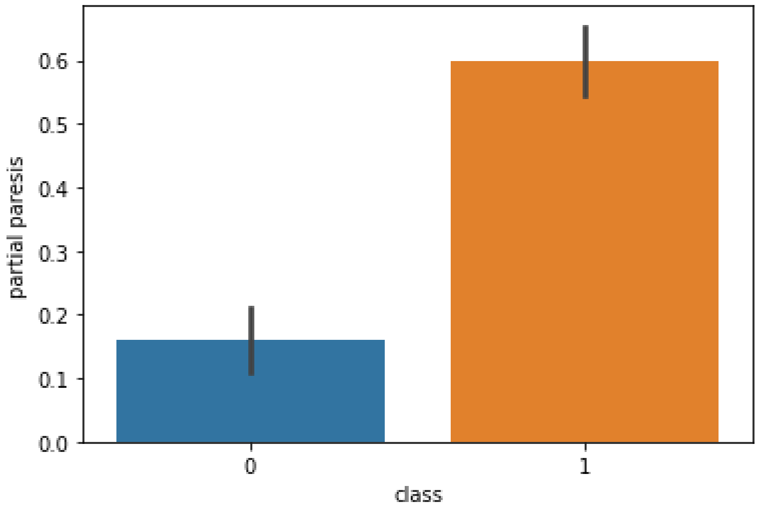
In [45]:
```
sns.barplot(x='class',y='delayed healing',data=diabetes_data_binary)
```

Out[45]: <matplotlib.axes._subplots.AxesSubplot at 0x2178b0925c8>



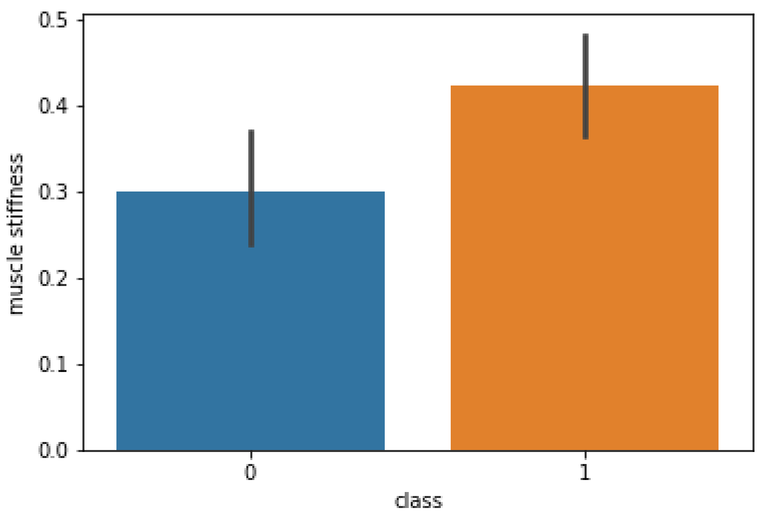
In [46]:
```
sns.barplot(x='class',y='partial paresis',data=diabetes_data_binary)
```

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x2178c896948>



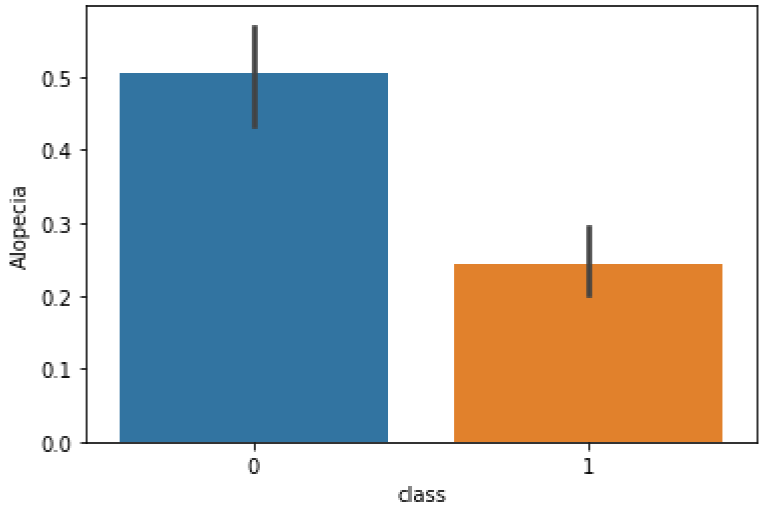
In [47]:
```
sns.barplot(x='class',y='muscle stiffness',data=diabetes_data_binary)
```

Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x2178c8e9dc8>



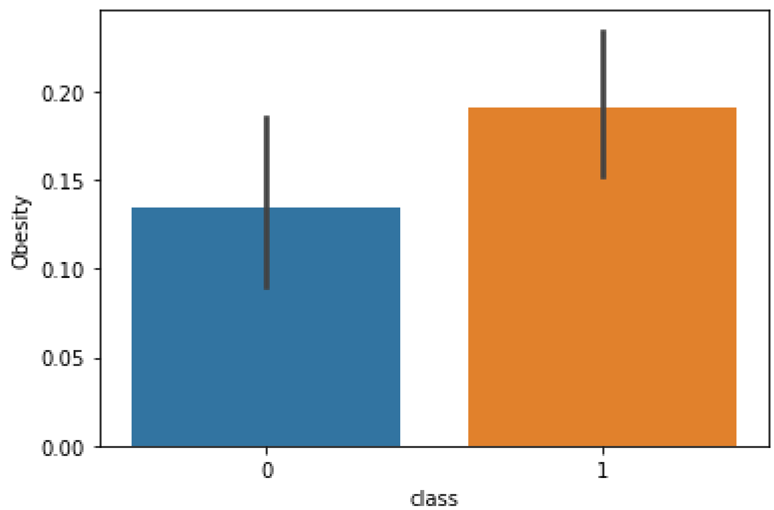
In [48]:
```
sns.barplot(x='class',y='Alopecia',data=diabetes_data_binary)
```

Out[48]: <matplotlib.axes._subplots.AxesSubplot at 0x2178c94abc8>



In [49]:
```
sns.barplot(x='class',y='Obesity',data=diabetes_data_binary)
```

Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x2178c9b1e88>



In [50]:
```
#most relevant variables seem to be Polyuria,Polydipsia,sudden weight loss,par
tial paresis,irritability for binary dataset
#most relevant variables for float dataset is Glucose, SkinThickness, Insulin,
and Age.
```

In [178]:
```
#Classification on diabetes/float dataset
#Some of the models the y_train needs to be reshaped using the ravel function
 or else a warning will appear
#No change to the models if use ravel code or not
```

In [52]:
```
# Partition dataset into training and validationg sets using 80-20 split
x_train, x_val, y_train, y_val = train_test_split(diabetes_data_floats.drop([
'Outcome'], axis=1), diabetes_data_floats[['Outcome']], test_size=0.2, random_
state=0)
```

In [53]:
```
print(x_train.shape)
print(y_train.shape)
print(x_val.shape)
print(y_val.shape)
```

```
(828, 8)
(828, 1)
(207, 8)
(207, 1)
```

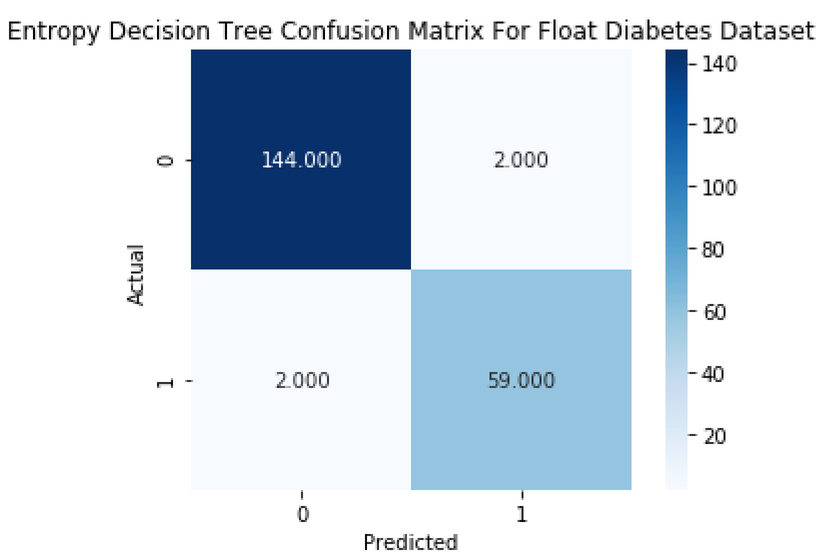
In [54]:
```
scaler = StandardScaler()
scaler.fit(x_train)
x_train_scaled = scaler.transform(x_train)
x_val_scaled = scaler.transform(x_val)
```

In [149]:
```
#Decision Trees using different criterions using the relevant variables found
 above
Eclassifier = DecisionTreeClassifier(criterion="entropy")
Eclassifier.fit(x_train_scaled[:, [1, 3, 4, 7]],y_train)
```

Out[149]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                       max_depth=None, max_features=None, max_leaf_nodes=Non
e,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

In [150]:
```
y_pred = Eclassifier.predict(x_val_scaled[:, [1, 3, 4, 7]])
```

In [151]:
```
conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Entropy Decision Tree Confusion Matrix For Float Diabetes Dataset')
plt.tight_layout()
```



In [152]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.9806763285024155, 0.019323671497584516, array([0.98630137, 0.96721311]), a
rray([0.98630137, 0.96721311]), array([0.98630137, 0.96721311])]
```

In [153]:
```
Eclassifier = DecisionTreeClassifier(criterion="gini")
Eclassifier.fit(x_train_scaled[:, [1, 3, 4, 7]],y_train)
```

Out[153]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=Non
e,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

In [154]:
```
y_pred = Eclassifier.predict(x_val_scaled[:, [1, 3, 4, 7]])
```

In [155]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.961352657004831, 0.03864734299516903, array([0.97260274, 0.93442623]), arr
ay([0.97260274, 0.93442623]), array([0.97260274, 0.93442623])]
```

In [156]:
```
#Entropy is better with a better accuracy and F1 score
```

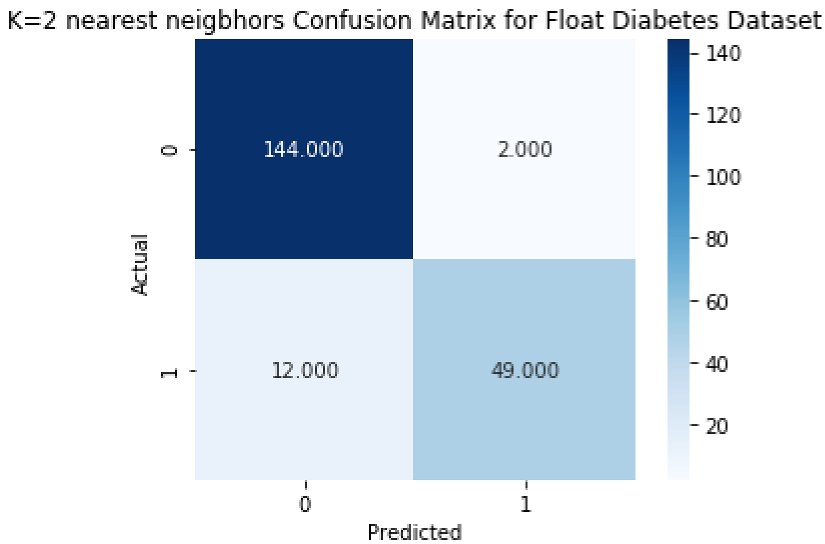
In [157]:
```
#K-nearest Neighbors
#Chose the best number of neighbors based of accuracy
neighbors = [2,3,5,10,15,25,50]
prevAccuracy = 0.0
myN = 0
for n in neighbors:
    classifier = KNeighborsClassifier(n_neighbors = n)
    classifier.fit(x_train_scaled[:, [1, 3, 4, 7]],y_train.values.ravel())
    y_pred = classifier.predict(x_val_scaled[:, [1, 3, 4, 7]])
    accuracy = metrics.accuracy_score(y_val,y_pred)
    if(accuracy > prevAccuracy):
        prevAccuracy = accuracy
        myN = n

print(myN)
```

```
2
```

In [158]:
```
#2 is the best number of neighbors based on accuracy ''
```

In [159]:
```
classifier = KNeighborsClassifier(n_neighbors = 2)
classifier.fit(x_train_scaled[:, [1, 3, 4, 7]],y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled[:, [1, 3, 4, 7]])
```

In [160]:
```
conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('K=2 nearest neigbhors Confusion Matrix for Float Diabetes Dataset')
plt.tight_layout()
```

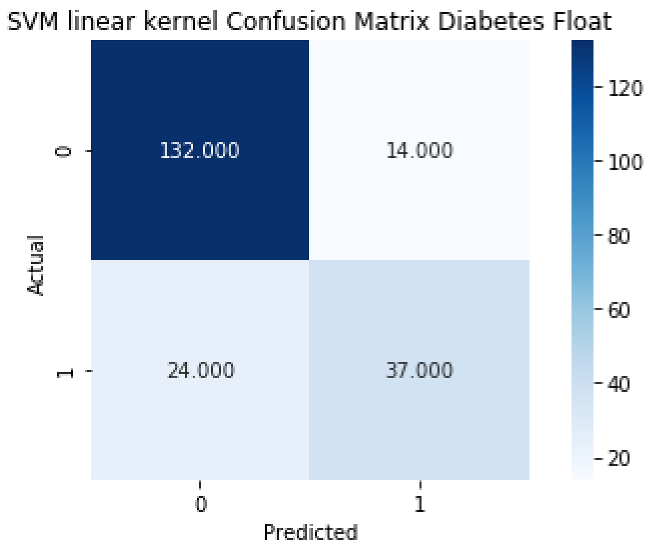


In [161]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.9323671497584541, 0.06763285024154586, array([0.92307692, 0.96078431]), ar
ray([0.98630137, 0.80327869]), array([0.95364238, 0.875     ])]
```

In [162]:
```
#Worse than the decision tree with entropy criterion
```

In [163]:
```
#Svm for float dataset
#Try to find the best kernel
classifier = SVC(kernel = 'linear')
classifier.fit(x_train_scaled[:, [1, 3, 4, 7]],y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled[:, [1, 3, 4, 7]])

conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('SVM linear kernel Confusion Matrix Diabetes Float')
plt.tight_layout()
```

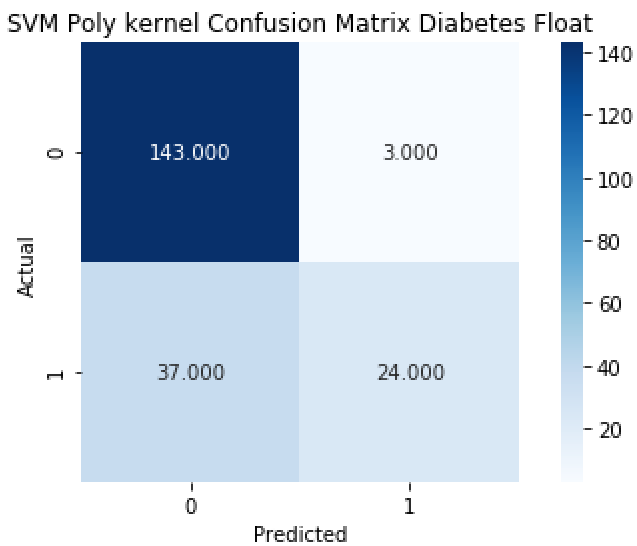


In [164]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.8164251207729468, 0.18357487922705318, array([0.84615385, 0.7254902 ]), ar
ray([0.90410959, 0.60655738]), array([0.87417219, 0.66071429])]
```

In [165]:
```
#Worse than both k-nearest neighbors and decision tree
```

In [167]:
```
classifier = SVC(kernel = 'poly')
classifier.fit(x_train_scaled[:, [1, 3, 4, 7]],y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled[:, [1, 3, 4, 7]])

conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('SVM Poly kernel Confusion Matrix Diabetes Float')
plt.tight_layout()
```

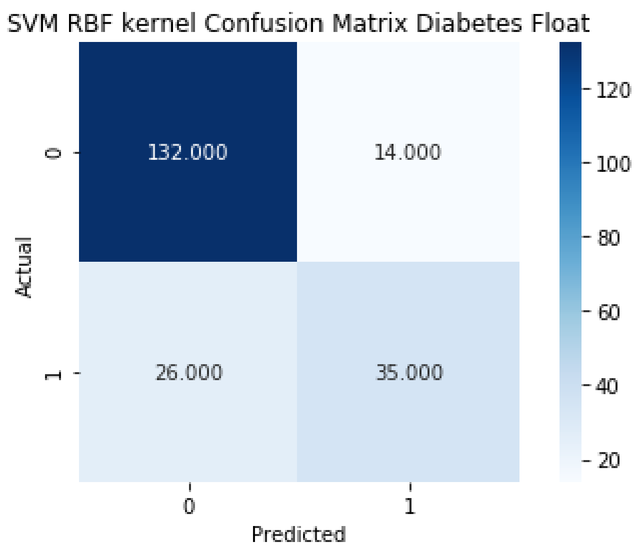


In [168]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.8067632850241546, 0.19323671497584538, array([0.79444444, 0.88888889]), ar
ray([0.97945205, 0.39344262]), array([0.87730061, 0.54545455])]
```

In [169]:
```
#Worse than linear kernel
```

In [170]:
```
classifier = SVC(kernel = 'rbf')
classifier.fit(x_train_scaled[:, [1, 3, 4, 7]],y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled[:, [1, 3, 4, 7]])

conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('SVM RBF kernel Confusion Matrix Diabetes Float')
plt.tight_layout()
```

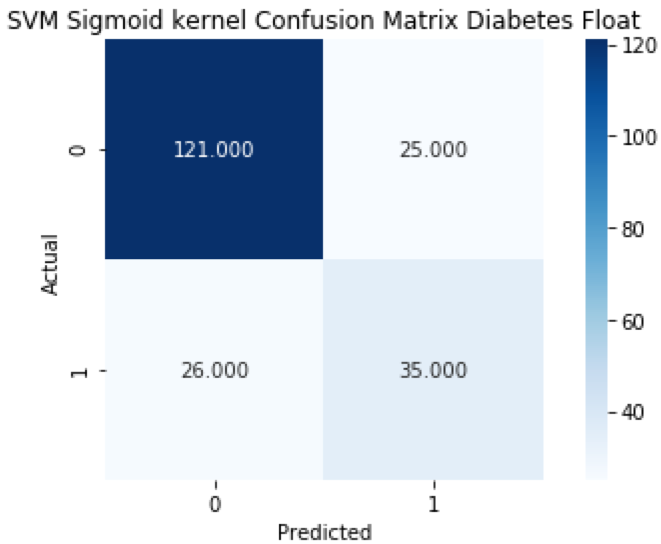


In [171]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.8067632850241546, 0.19323671497584538, array([0.83544304, 0.71428571]), ar
ray([0.90410959, 0.57377049]), array([0.86842105, 0.63636364])]
```

In [172]:
```
#Worse than linear but better than rbf with the F1 score. Decision tree is sti
ll best so far
```

In [173]:
```
classifier = SVC(kernel = 'sigmoid')
classifier.fit(x_train_scaled[:, [1, 3, 4, 7]],y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled[:, [1, 3, 4, 7]])

conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('SVM Sigmoid kernel Confusion Matrix Diabetes Float')
plt.tight_layout()
```



In [174]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.7536231884057971, 0.24637681159420288, array([0.82312925, 0.58333333]), ar
ray([0.82876712, 0.57377049]), array([0.82593857, 0.5785124 ])]
```

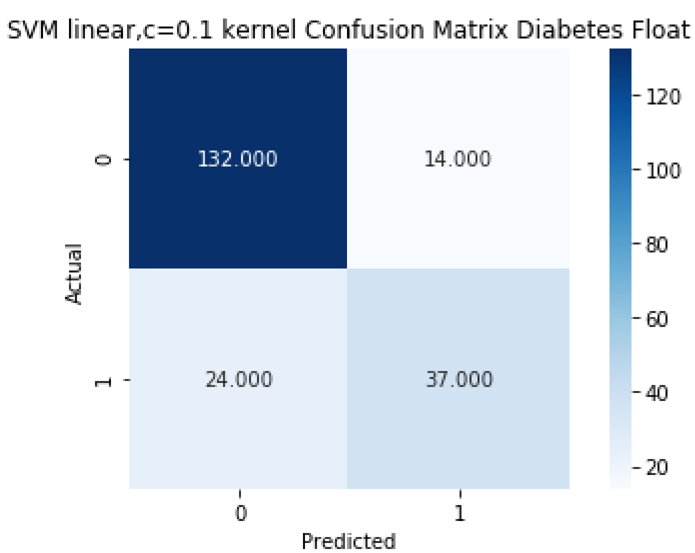
In [175]:
```
#The worst kernel. The best kernel is linear, best model so far is decision tr
ee
```

In [176]:
```
# Now try to find the best c value
# based on accuracy
values = [0.001,0.01,0.1,0.5,1.0,5.0,10]
prevAcc = 0.0
cVal = -1
for v in values:
    classifier = SVC(kernel = 'linear', C = v)
    classifier.fit(x_train_scaled[:, [1, 3, 4, 7]],y_train.values.ravel())
    y_pred = classifier.predict(x_val_scaled[:, [1, 3, 4, 7]])
    accuracy = metrics.accuracy_score(y_val,y_pred)
    if(accuracy > prevAcc):
        prevAcc = accuracy
        cVal = v
print(cVal)
```

```
0.1
```

In [197]:
```
# best C val = 0.1
classifier = SVC(kernel = 'linear', C = 0.1)
classifier.fit(x_train_scaled[:, [1, 3, 4, 7]],y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled[:, [1, 3, 4, 7]])
```

In [198]:
```
conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('SVM linear,c=0.1 kernel Confusion Matrix Diabetes Float')
plt.tight_layout()
```



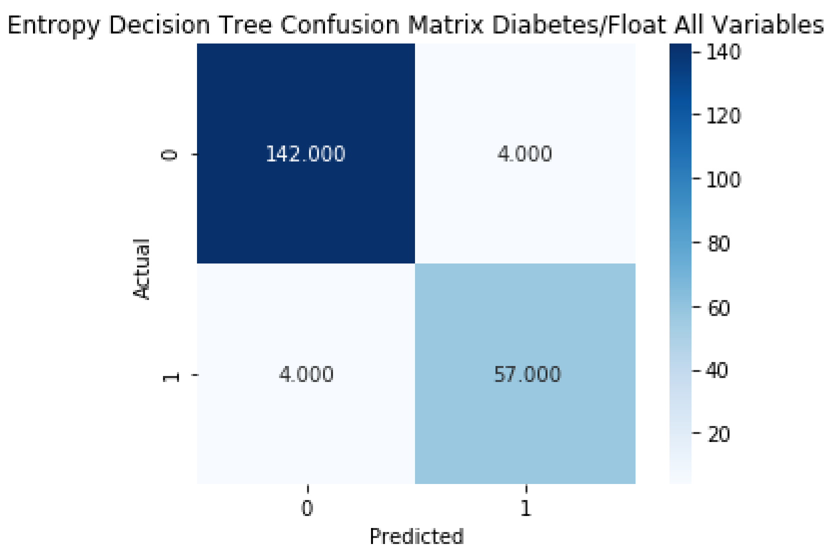
In [199]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.8164251207729468, 0.18357487922705318, array([0.84615385, 0.7254902 ]), ar
ray([0.90410959, 0.60655738]), array([0.87417219, 0.66071429])]
```

In [182]:
```
#The best svm model is still not as good as decision tree
```

In [183]:
```
#Lets try the best models for each classification using all the variables to s
ee if they give any extra insight.
#Decision Trees using different criterions using the relevant variables found
 above
Eclassifier = DecisionTreeClassifier(criterion="entropy")
Eclassifier.fit(x_train_scaled,y_train)
y_pred = Eclassifier.predict(x_val_scaled)
```

In [184]:
```
conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Entropy Decision Tree Confusion Matrix Diabetes/Float All Variable
s')
plt.tight_layout()
```



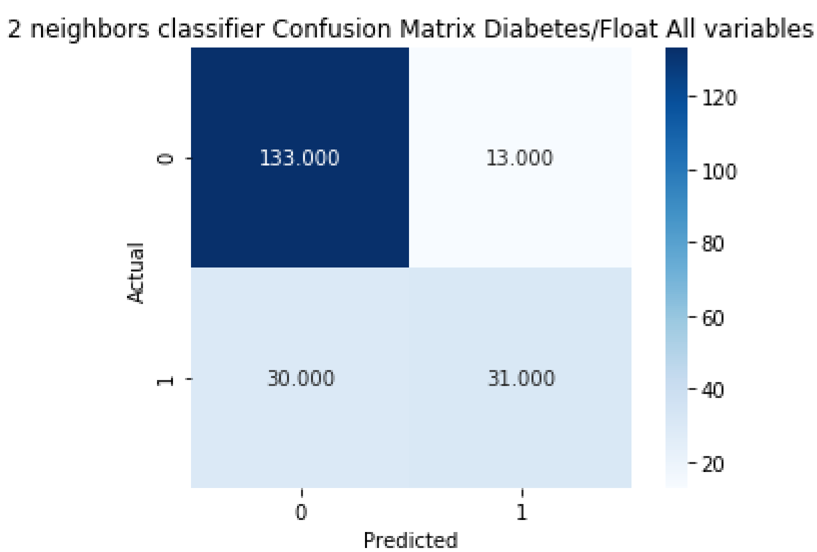
In [185]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.961352657004831, 0.03864734299516903, array([0.97260274, 0.93442623]), arr
ay([0.97260274, 0.93442623]), array([0.97260274, 0.93442623])]
```

In [91]:
```
#This model performs slightly worse than the other decision tree model with th
e subset of variables
```

In [186]:
```
# K=2 nearest neighbors with a c val of 0.1. All variables
classifier = KNeighborsClassifier(n_neighbors = 2)
classifier.fit(x_train_scaled,y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled)
```

In [189]:
```
conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title("2 neighbors classifier Confusion Matrix Diabetes/Float All variable
s")
plt.tight_layout()
```

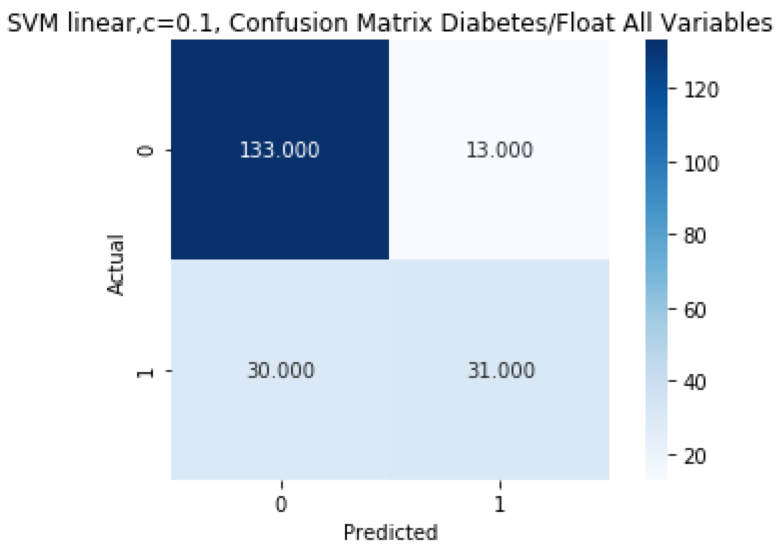


In [190]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.7922705314009661, 0.20772946859903385, array([0.81595092, 0.70454545]), ar
ray([0.9109589 , 0.50819672]), array([0.86084142, 0.59047619])]
```

In [191]:
```
#Significantly worse model than the original subset of variables
```

In [195]:
```
#SVM all variables
classifier = SVC(kernel = 'linear',C=0.1)
classifier.fit(x_train_scaled,y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled)

conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('SVM linear,c=0.1, Confusion Matrix Diabetes/Float All Variables')
plt.tight_layout()
```



In [196]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.7922705314009661, 0.20772946859903385, array([0.81595092, 0.70454545]), ar
ray([0.9109589 , 0.50819672]), array([0.86084142, 0.59047619])]
```

In [200]:
```
#Slightly worse than the original subset counterpart model
```

In [201]:
```
#Best model for the diabetes float is decision tree subset of variables with e
ntropy criterion.
```

In [ ]:
```

```

In [202]:
```
#Run classification techniques on the binary dataset
# Partition dataset into training and validationg sets using 80-20 split
x_train, x_val, y_train, y_val = train_test_split(diabetes_data_binary.drop([
'class'], axis=1), diabetes_data_binary[['class']], test_size=0.2, random_stat
e=0)
```

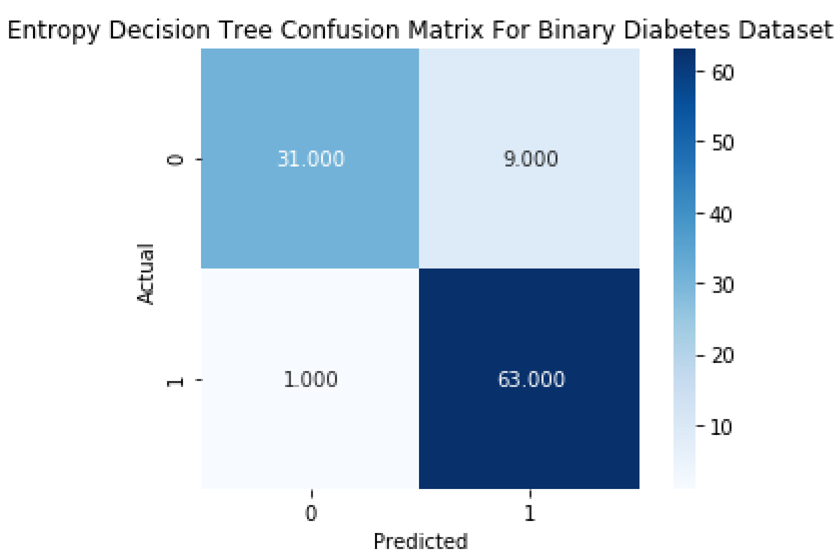
In [203]:
```
scaler = StandardScaler()
scaler.fit(x_train)
x_train_scaled = scaler.transform(x_train)
x_val_scaled = scaler.transform(x_val)
```

In [204]:
```
#Decision Trees using different criterions using the relevant variables found
 above
Eclassifier = DecisionTreeClassifier(criterion="entropy")
Eclassifier.fit(x_train_scaled[:, [2, 3, 4, 10,12]],y_train)
```

Out[204]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                       max_depth=None, max_features=None, max_leaf_nodes=Non
e,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

In [205]:
```
y_pred = Eclassifier.predict(x_val_scaled[:, [2, 3, 4, 10,12]])
```

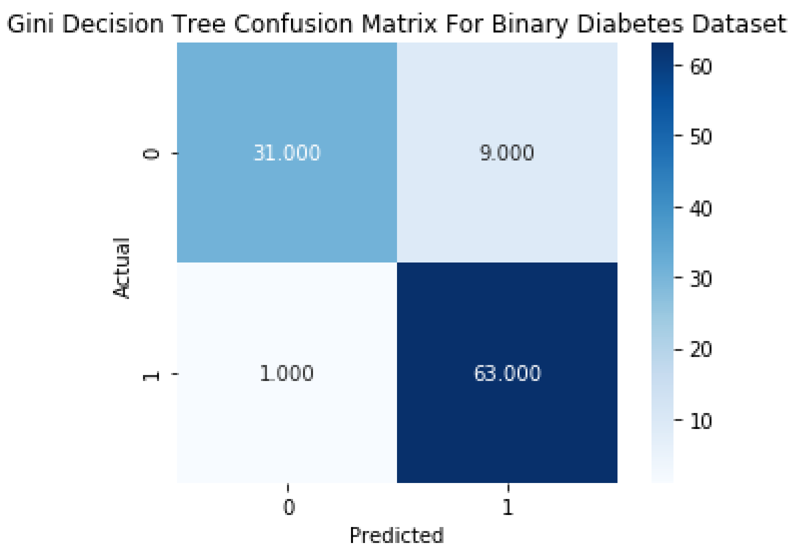
In [207]:
```
conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Entropy Decision Tree Confusion Matrix For Binary Diabetes Dataset'
)
plt.tight_layout()
```



In [208]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.9038461538461539, 0.09615384615384615, array([0.96875, 0.875  ]), array
([0.775   , 0.984375]), array([0.86111111, 0.92647059])]
```

In [211]:
```
#Now see gini criterion
Eclassifier = DecisionTreeClassifier(criterion="gini")
Eclassifier.fit(x_train_scaled[:, [2, 3, 4, 10,12]],y_train)
y_pred = Eclassifier.predict(x_val_scaled[:, [2, 3, 4, 10,12]])
conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Gini Decision Tree Confusion Matrix For Binary Diabetes Dataset')
plt.tight_layout()
```



In [212]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

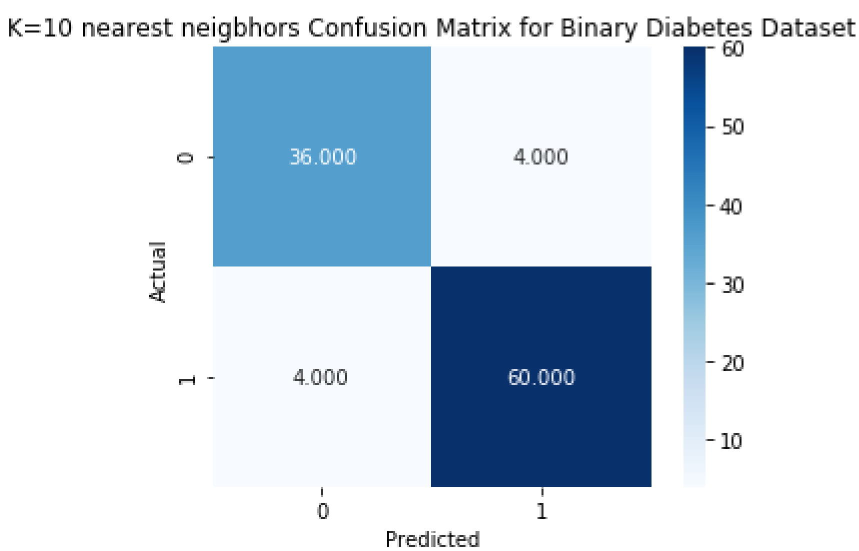
```
[0.9038461538461539, 0.09615384615384615, array([0.96875, 0.875  ]), array
([0.775   , 0.984375]), array([0.86111111, 0.92647059])]
```

In [213]:
```
#Exactly the same most likely due to the fact these values are binary
```

In [214]:
```
#K-nearest Neighbors
#Chose the best number of neighbors based of accuracy
neighbors = [2,3,5,10,15,25,50]
prevAccuracy = 0.0
myN = 0
for n in neighbors:
    classifier = KNeighborsClassifier(n_neighbors = n)
    classifier.fit(x_train_scaled[:, [2, 3, 4, 10,12]],y_train.values.ravel())
    y_pred = classifier.predict(x_val_scaled[:, [2, 3, 4, 10,12]])
    accuracy = metrics.accuracy_score(y_val,y_pred)
    if(accuracy > prevAccuracy):
        prevAccuracy = accuracy
        myN = n

print(myN)
```

```
10
```

In [217]:
```
#10 neighbors are the best here

classifier = KNeighborsClassifier(n_neighbors = 10)
classifier.fit(x_train_scaled[:, [2, 3, 4, 10,12]],y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled[:, [2, 3, 4, 10, 12]])
conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('K=10 nearest neigbhors Confusion Matrix for Binary Diabetes Datase
t')
plt.tight_layout()
```

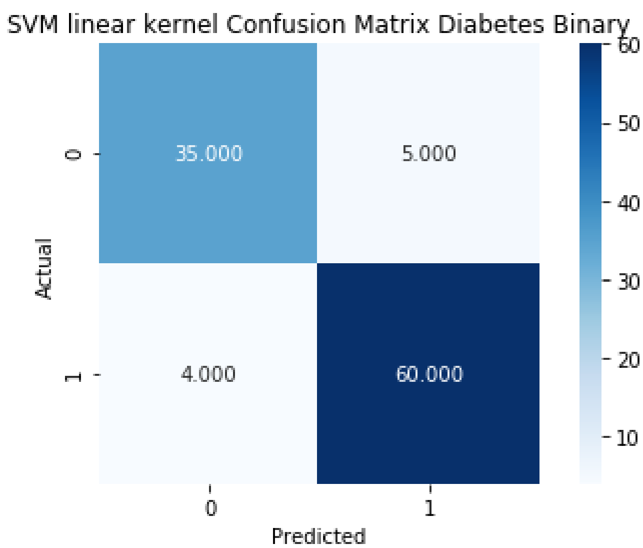


In [218]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.9230769230769231, 0.07692307692307687, array([0.9   , 0.9375]), array([0.9
, 0.9375]), array([0.9   , 0.9375])]
```

In [219]:
```
#Better than the decision tree results in accuracy and F1 score
```

In [223]:
```
#Lets try SVMs
classifier = SVC(kernel = 'linear')
classifier.fit(x_train_scaled[:, [2, 3, 4, 10,12]],y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled[:, [2, 3, 4, 10,12]])

conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('SVM linear kernel Confusion Matrix Diabetes Binary')
plt.tight_layout()
```

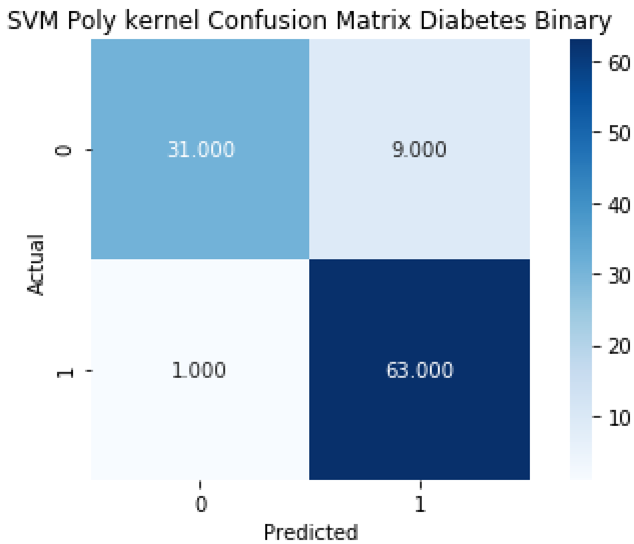


In [224]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.9134615384615384, 0.08653846153846156, array([0.8974359 , 0.92307692]), ar
ray([0.875 , 0.9375]), array([0.88607595, 0.93023256])]
```

In [225]:
```
#Slightly better than decision tree and slightly worse than k-nearest neighbor
s
```

In [226]:
```
classifier = SVC(kernel = 'poly')
classifier.fit(x_train_scaled[:, [2, 3, 4, 10,12]],y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled[:, [2, 3, 4, 10, 12]])

conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('SVM Poly kernel Confusion Matrix Diabetes Binary')
plt.tight_layout()
```

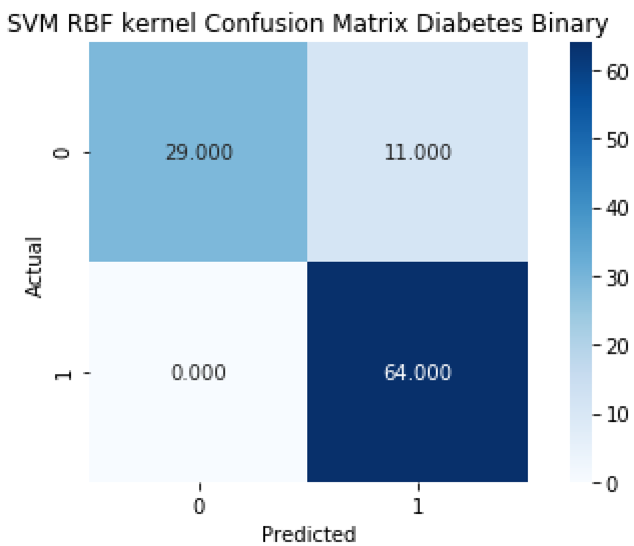


In [227]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.9038461538461539, 0.09615384615384615, array([0.96875, 0.875  ]), array
([0.775   , 0.984375]), array([0.86111111, 0.92647059])]
```

In [228]:
```
#About the same as decision trees, but worse than linear svm
```

In [229]:
```
classifier = SVC(kernel = 'rbf')
classifier.fit(x_train_scaled[:, [2, 3, 4, 10,12]],y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled[:, [2, 3, 4, 10,12]])

conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('SVM RBF kernel Confusion Matrix Diabetes Binary')
plt.tight_layout()
```

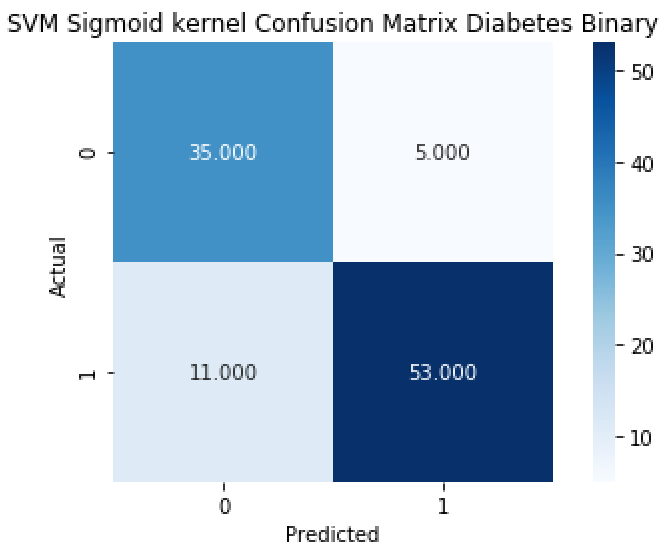


In [230]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.8942307692307693, 0.10576923076923073, array([1.        , 0.85333333]), ar
ray([0.725, 1.   ]), array([0.84057971, 0.92086331])]
```

In [231]:
```
#Worst model so far
```

In [232]:
```
classifier = SVC(kernel = 'sigmoid')
classifier.fit(x_train_scaled[:, [2, 3, 10, 12]],y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled[:, [2, 3, 10, 12]])

conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('SVM Sigmoid kernel Confusion Matrix Diabetes Binary')
plt.tight_layout()
```



In [233]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.8461538461538461, 0.15384615384615385, array([0.76086957, 0.9137931 ]), ar
ray([0.875    , 0.828125]), array([0.81395349, 0.86885246])]
```

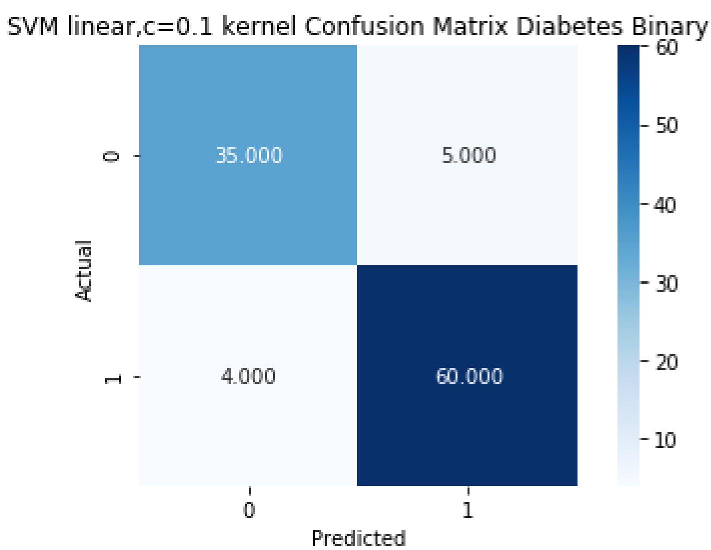
In [234]:
```
#This is the worst model seen so far and the worst kernel.
```

In [235]:
```
# Now try to find the best c value
# based on accuracy
values = [0.001,0.01,0.1,0.5,1.0,5.0,10]
prevAcc = 0.0
cVal = -1
for v in values:
    classifier = SVC(kernel = 'linear', C = v)
    classifier.fit(x_train_scaled[:, [2, 3, 4, 10,12]],y_train.values.ravel())
    y_pred = classifier.predict(x_val_scaled[:, [2, 3, 4, 10,12]])
    accuracy = metrics.accuracy_score(y_val,y_pred)
    if(accuracy > prevAcc):
        prevAcc = accuracy
        cVal = v
print(cVal)
```

```
0.1
```

In [236]:
```
#Best c val is 0.1 and best kernel is linear
classifier = SVC(kernel = 'linear', C = 0.1)
classifier.fit(x_train_scaled[:, [2, 3, 4, 10, 12]],y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled[:, [2, 3, 4, 10, 12]])
```

In [237]:
```
conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('SVM linear,c=0.1 kernel Confusion Matrix Diabetes Binary')
plt.tight_layout()
```

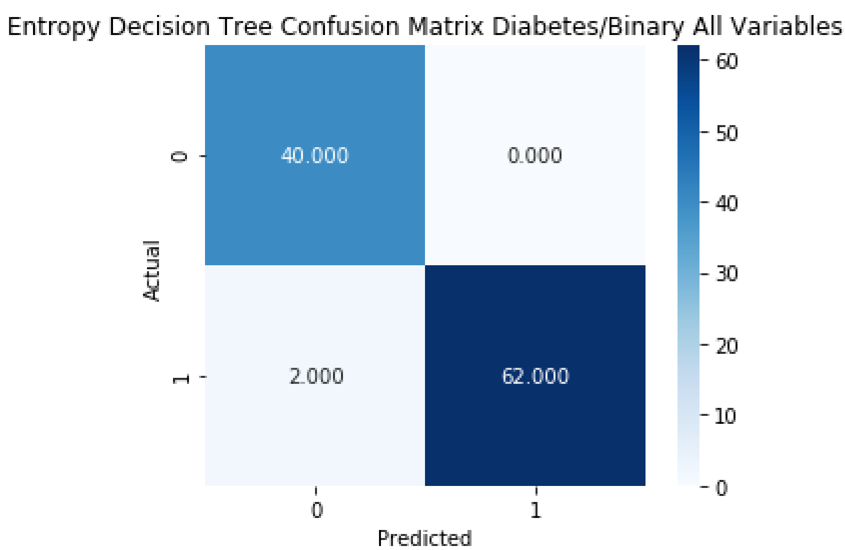


In [238]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.9134615384615384, 0.08653846153846156, array([0.8974359 , 0.92307692]), ar
ray([0.875 , 0.9375]), array([0.88607595, 0.93023256])]
```

In [239]:
```
#Around the same as decision tree. Slightly worse than K nearest neighbors wit
h slightly less accuracy
# and F1 score is also less than k nearest neighbors
```

In [240]:
```
#Lets see if including all variable will give any insight
#For decision tree it doesnt matter which one to choose
Eclassifier = DecisionTreeClassifier(criterion="entropy")
Eclassifier.fit(x_train_scaled,y_train)
y_pred = Eclassifier.predict(x_val_scaled)

conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Entropy Decision Tree Confusion Matrix Diabetes/Binary All Variable
s')
plt.tight_layout()
```

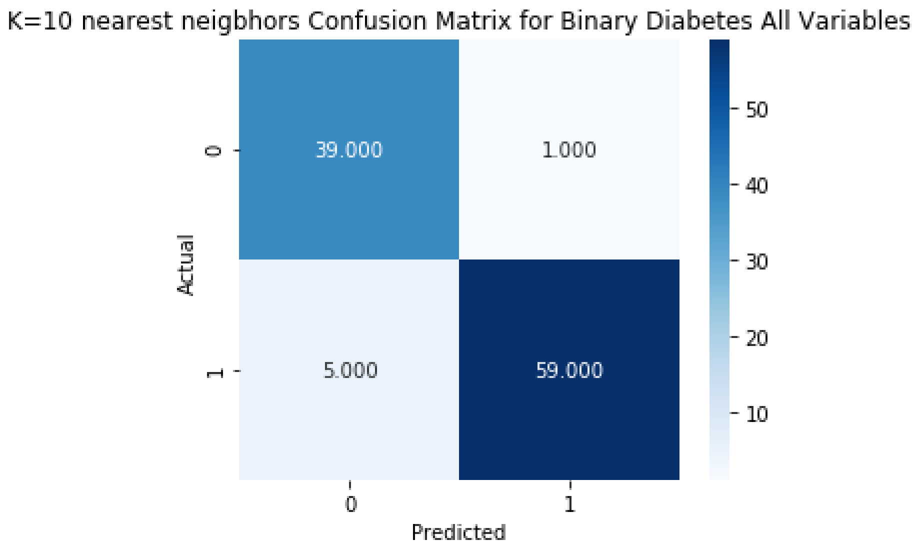


In [241]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.9807692307692307, 0.019230769230769273, array([0.95238095, 1.        ]), a
rray([1.        , 0.96875]), array([0.97560976, 0.98412698])]
```

In [242]:
```
#Much better this time. With the highest accuracy and F1 score yet.
```

In [245]:
```
classifier = KNeighborsClassifier(n_neighbors = 10)
classifier.fit(x_train_scaled,y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled)
conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('K=10 nearest neigbhors Confusion Matrix for Binary Diabetes All Var
iables')
plt.tight_layout()
```

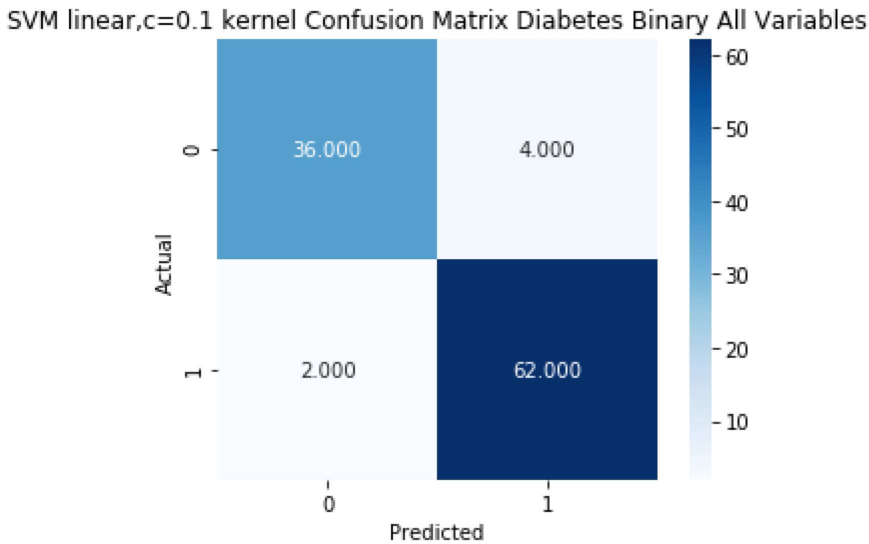


In [246]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.9423076923076923, 0.05769230769230771, array([0.88636364, 0.98333333]), ar
ray([0.975    , 0.921875]), array([0.92857143, 0.9516129 ])]
```

In [247]:
```
#Slightly better than the original subset but not as good as entropy with all
 variables
```

In [248]:
```
classifier = SVC(kernel = 'linear', C = 0.1)
classifier.fit(x_train_scaled,y_train.values.ravel())
y_pred = classifier.predict(x_val_scaled)
conf_matrix = metrics.confusion_matrix(y_val,y_pred)
sns.heatmap(conf_matrix,annot=True,fmt=".3f",square = True, cmap = plt.cm.Blue
s)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('SVM linear,c=0.1 kernel Confusion Matrix Diabetes Binary All Variab
les')
plt.tight_layout()
```



In [249]:
```
accuracy = metrics.accuracy_score(y_val,y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val,y_pred,average = None)
recall = metrics.recall_score(y_val,y_pred,average=None)
F1_score = metrics.f1_score(y_val,y_pred,average = None)
print([accuracy,error,precision,recall,F1_score])
```

```
[0.9423076923076923, 0.05769230769230771, array([0.94736842, 0.93939394]), ar
ray([0.9    , 0.96875]), array([0.92307692, 0.95384615])]
```

In [ ]:
```
#Better model than original subset of variables but still decision tree with a
ll variables is the best.
#Best model is decision tree with all variables
```