In [1]:
```
import numpy as np
import pandas as pd
pd.pandas.set_option('display.max_columns',None)

import seaborn as sns
sns.set(font_scale=1.2)

import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (12,8)
%matplotlib inline

import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
```

Load dataset

In [2]:
```
df = pd.read_csv(r'part6\Historical Weather Data 2010-2021_preprocessed_1.cs
df.head()
```

Out[2]:

	observation	date	month	year	tempC_7to8	tempC_1to2	tempC_6to7	tempC_avg(0C)	R humidit
0	2010-01-01	1	1	2010	20	30	20	23	
1	2010-01-02	2	1	2010	23	29	23	25	
2	2010-01-03	3	1	2010	24	27	21	24	
3	2010-01-04	4	1	2010	23	29	20	24	
4	2010-01-05	5	1	2010	22	30	21	24	

In [3]:
```
# columns name
print(list(df.columns))
```

```
['observation', 'date', 'month', 'year', 'tempC_7to8', 'tempC_1to2', 'tempC_6to
7', 'tempC_avg(0C)', 'Relative humidity_7to8', 'Relative humidity_1to2', 'Relat
ive humidity_6to7', 'Relative humidity_avg(%)', 'windspeedKmph_7to8', 'windspee
dKmph_1to2', 'windspeedKmph_6to7', 'windspeedKmph_avg(Km/h)', 'pressureMB_7to
8', 'pressureMB_1to2', 'pressureMB_6to7', 'pressureMB_avg', 'precipMM_7to8', 'p
recipMM_1to2', 'precipMM_6to7', 'precipMM_avg(mm)', 'weatherDesc_7to8', 'weathe
rDesc_1to2', 'weatherDesc_6to7', 'weatherDesc', 'Sunshine Hours', '%_soil_moisu
re', 'soil_pH', 'water_pH', 'water_TDS_mgpl', 'Label (Disease Yes/No)', 'Type o
f Disease (Bacterial Blight/Telya)', 'Anthracnose', 'Fruit Spot/ Rot', 'Fusariu
m Wilt', 'Fruit Borer / Blight Blora']
```

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

```
 21  precipMM_1to2                          4227 non-null   float64
 22  precipMM_6to7                          4227 non-null   float64
 23  precipMM_avg(mm)                       4227 non-null   float64
 24  weatherDesc_7to8                       4227 non-null   int64
 25  weatherDesc_1to2                       4227 non-null   int64
 26  weatherDesc_6to7                       4227 non-null   int64
 27  weatherDesc                            4227 non-null   int64
 28  Sunshine Hours                         4227 non-null   float64
 29  %_soil_moisure                         4227 non-null   int64
 30  soil_pH                                4227 non-null   float64
 31  water_pH                               4227 non-null   float64
 32  water_TDS_mgpl                         4227 non-null   float64
 33  Label (Disease Yes/No)                 4227 non-null   int64
 34  Type of Disease (Bacterial Blight/Telya) 4227 non-null   int64
 35  Anthracnose                            4227 non-null   int64
 36  Fruit Spot/ Rot                        4227 non-null   int64
 37  Fusarium Wilt                          4227 non-null   int64
 38  Fruit Borer / Blight Blora             4227 non-null   int64
dtypes: float64(8), int64(30), object(1)
memory usage: 1.3+ MB
```

Feature Selection

Filter features by variance

In [5]:
```
for val in range(len(df.iloc[:, :-6].var())):
    if (df.iloc[:, :-6].var()[val] < 1):
        print(val, df.iloc[:, :-6].var().keys()[val], df.iloc[:, :-6].var()[
#         print(df.iloc[:, :-6].var().keys()[val], end=', ')
```

```
19 precipMM_7to8 0.08410490512896031
20 precipMM_1to2 0.11755641594146687
21 precipMM_6to7 0.619745075126642
22 precipMM_avg(mm) 0.14154237379454246
23 weatherDesc_7to8 0.7532171823551971
29 soil_pH 0.06578349177548583
30 water_pH 0.2503095181954714
```

Observation:

- precipMM_7to8, precipMM_1to2, precipMM_6to7, precipMM_avg(mm), weatherDesc_7to8, soil_pH, water_pH show's less than 1 variance, So we can eliminate its.

In [6]:
```
df_without_less_variance = df.drop(columns = ['precipMM_7to8', 'precipMM_1to
                                              'weatherDesc_7to8', 'soil_pH',

df_without_less_variance.shape
```

Out[6]:
```
(4227, 32)
```

Filter features by correlation

Pairwise correlation

In [7]:
```
# sns.pairplot(df.iloc[:, :-6])
```

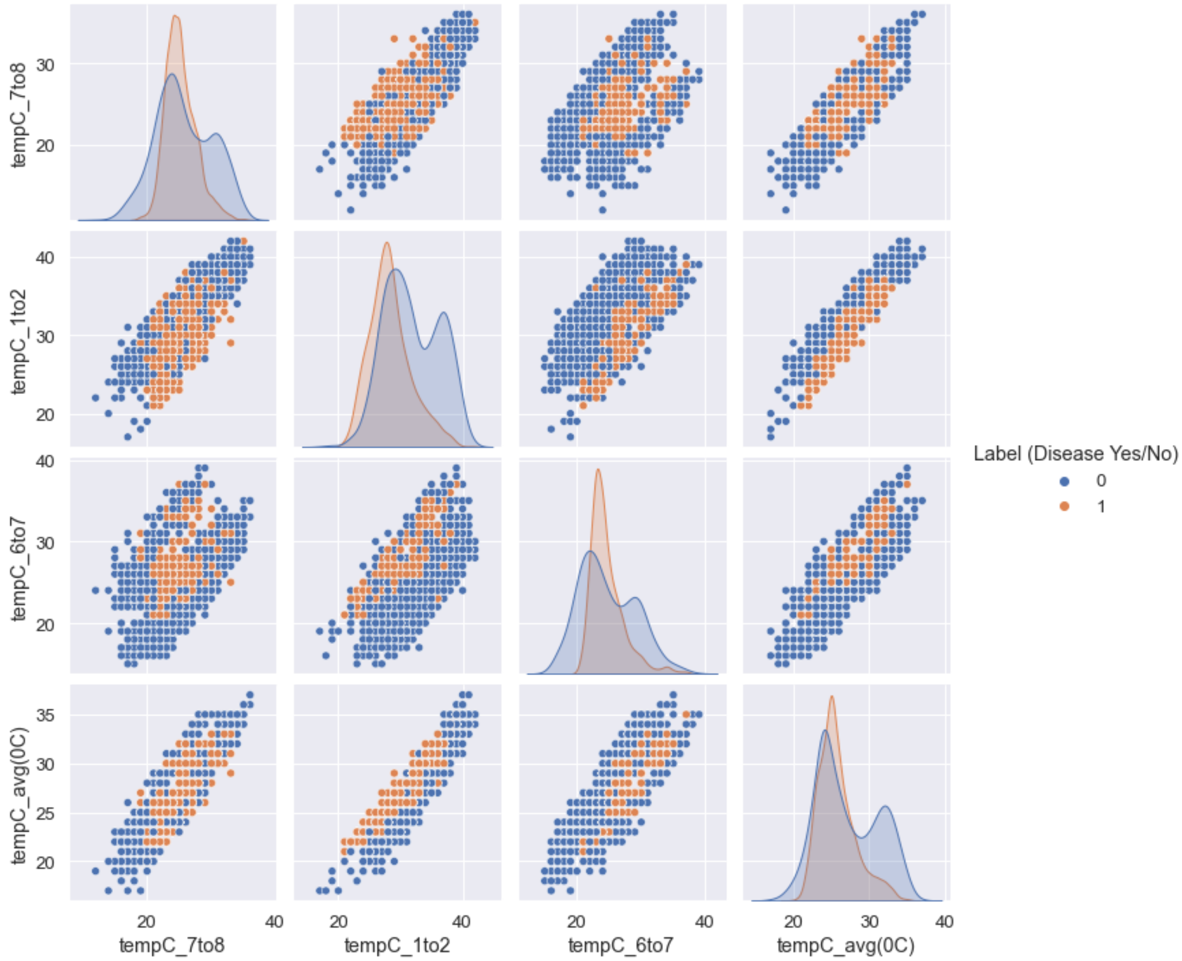
Pairwise correlation in temp

In [8]:

```
from scipy.stats import pearsonr

df_temp = df[['tempC_7to8', 'tempC_1to2', 'tempC_6to7', 'tempC_avg(0C)', 'La
display(df_temp.corr())
sns.pairplot(df_temp, hue = 'Label (Disease Yes/No)')

for col in df_temp.columns[:-1]:
    print(f"Pearson correlation between {col} & Label (Disease Yes/No) is :
{round(pearsonr(df_temp[col], df_temp['Label (Disease Yes/No)'])[0]*100,2)}

```

	tempC_7to8	tempC_1to2	tempC_6to7	tempC_avg(0C)	Label (Disease Yes/No)
tempC_7to8	1.000000	0.794591	0.609636	0.891016	-0.071696
tempC_1to2	0.794591	1.000000	0.684452	0.930440	-0.393744
tempC_6to7	0.609636	0.684452	1.000000	0.849070	-0.012142
tempC_avg(0C)	0.891016	0.930440	0.849070	1.000000	-0.188397
Label (Disease Yes/No)	-0.071696	-0.393744	-0.012142	-0.188397	1.000000

```
Pearson correlation between tempC_7to8 & Label (Disease Yes/No) is : -7.17 %
Pearson correlation between tempC_1to2 & Label (Disease Yes/No) is : -39.37 %
Pearson correlation between tempC_6to7 & Label (Disease Yes/No) is : -1.21 %
Pearson correlation between tempC_avg(0C) & Label (Disease Yes/No) is : -18.84
%
```



Observation:

- The all temp columns are highly correlated with each other (> 50%)
- The correlation between tempC_1to2 & Label (Disease Yes/No) is -39.37% (-ve correlation)
- The correlation between tempC_avg(0C) & Label (Disease Yes/No) is -18.84% (-ve correlation)
- So, we can keep tempC_1to2 or tempC_avg(0C)

In [9]:

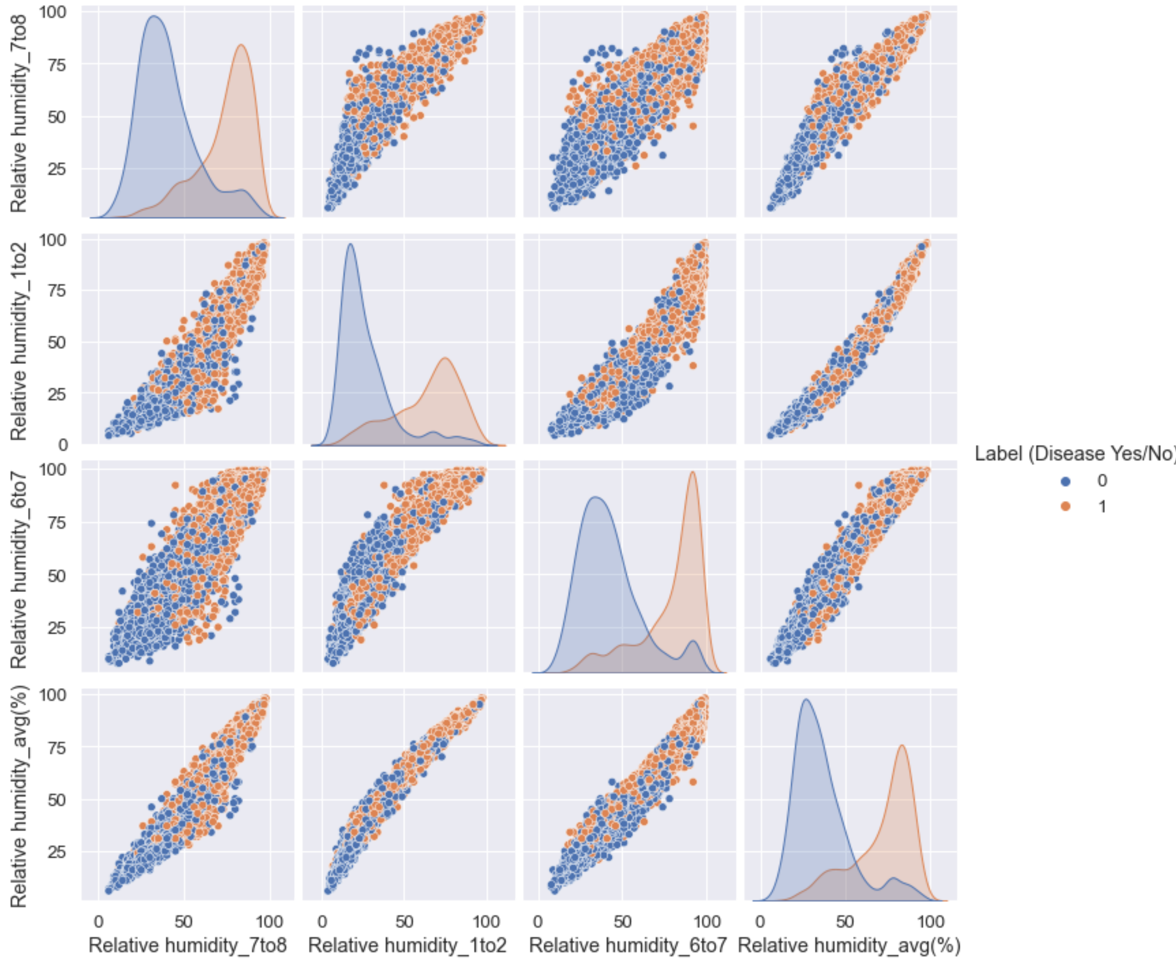
```
def get_Pairwise_Correlation(cols, hue_col):
    df_temp = df[cols]
    display(df_temp.corr())
    sns.pairplot(df_temp, hue = hue_col)

    for col in df_temp.columns[:-1]:
        print(f"Pearson correlation between {col} & {hue_col} is : {round(pe

```

Pairwise correlation in humidity

In [10]:
```
cols = ['Relative humidity_7to8', 'Relative humidity_1to2', 'Relative humidi
hue_col = cols[-1]
get_Pairwise_Correlation(cols, hue_col)
```

	Relative humidity_7to8	Relative humidity_1to2	Relative humidity_6to7	Relative humidity_avg(%)	Label (Disease Yes/No)
Relative humidity_7to8	1.000000	0.947885	0.921824	0.974510	0.698479
Relative humidity_1to2	0.947885	1.000000	0.952480	0.986800	0.707830
Relative humidity_6to7	0.921824	0.952480	1.000000	0.978579	0.695503
Relative humidity_avg(%)	0.974510	0.986800	0.978579	1.000000	0.714930
Label (Disease Yes/No)	0.698479	0.707830	0.695503	0.714930	1.000000

```
Pearson correlation between Relative humidity_7to8 & Label (Disease Yes/No) is
: 69.85%
Pearson correlation between Relative humidity_1to2 & Label (Disease Yes/No) is
: 70.78%
Pearson correlation between Relative humidity_6to7 & Label (Disease Yes/No) is
: 69.55%
Pearson correlation between Relative humidity_avg(%) & Label (Disease Yes/No) i
s : 71.49%
```



Observation:

- The all humidity columns are highly correlated with each other (> 50%)
- The correlation between Relative humidity_avg(%) & Label (Disease Yes/No) is 71.49% (+ve correlation)
- So, we can keep Relative humidity_avg(%)

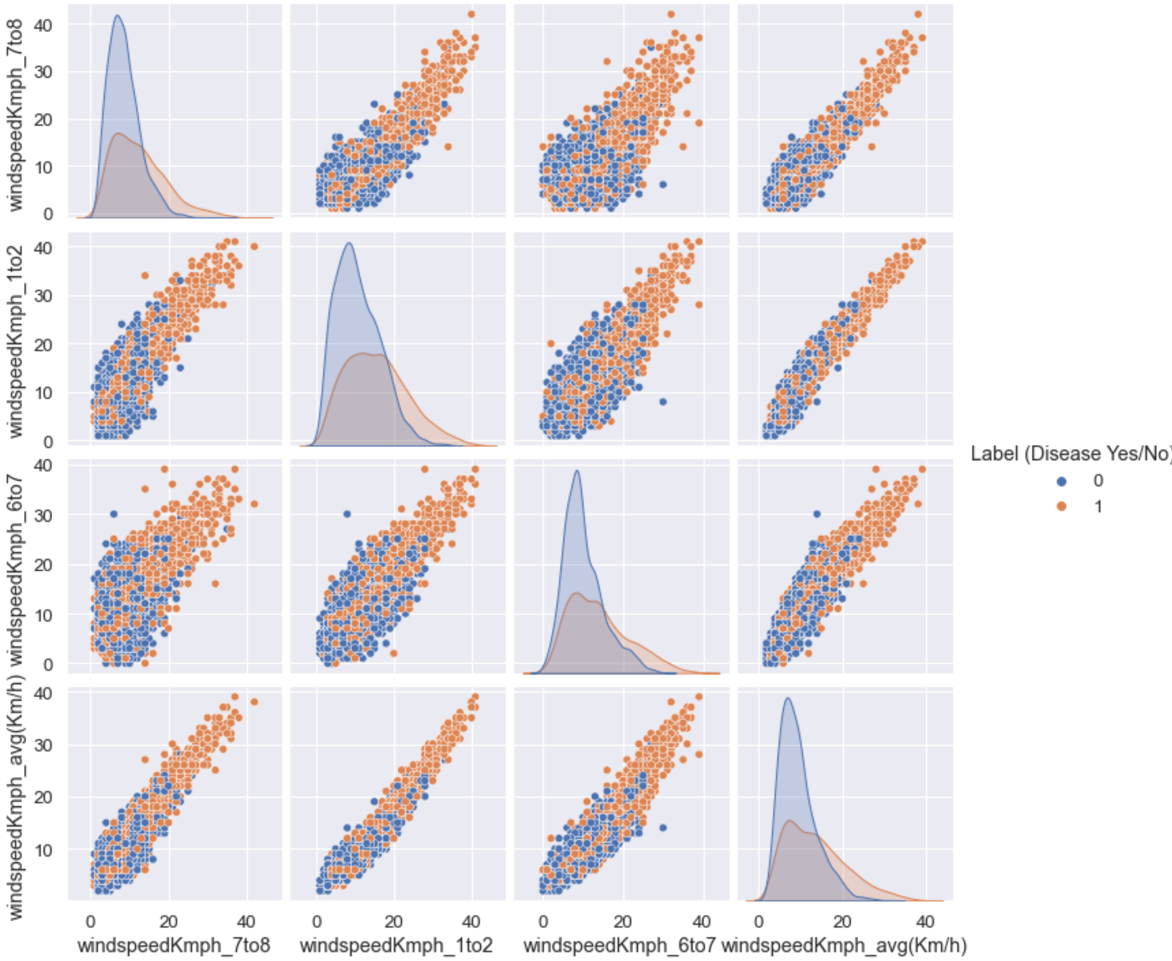
Pairwise correlation in windspeed

In [11]:

```
cols = ['windspeedKmph_7to8', 'windspeedKmph_1to2', 'windspeedKmph_6to7', 'w
hue_col = cols[-1]
get_Pairwise_Correlation(cols, hue_col)
```

	windspeedKmph_7to8	windspeedKmph_1to2	windspeedKmph_6to7	win
windspeedKmph_7to8	1.000000	0.839478	0.740329	
windspeedKmph_1to2	0.839478	1.000000	0.844685	
windspeedKmph_6to7	0.740329	0.844685	1.000000	
windspeedKmph_avg(Km/h)	0.913386	0.961066	0.923829	
Label (Disease Yes/No)	0.327046	0.332969	0.286785	

```
Pearson correlation between windspeedKmph_7to8 & Label (Disease Yes/No) is : 3
2.7%
Pearson correlation between windspeedKmph_1to2 & Label (Disease Yes/No) is : 3
3.3%
Pearson correlation between windspeedKmph_6to7 & Label (Disease Yes/No) is : 2
8.68%
Pearson correlation between windspeedKmph_avg(Km/h) & Label (Disease Yes/No) is
: 33.78%
```



Observation:

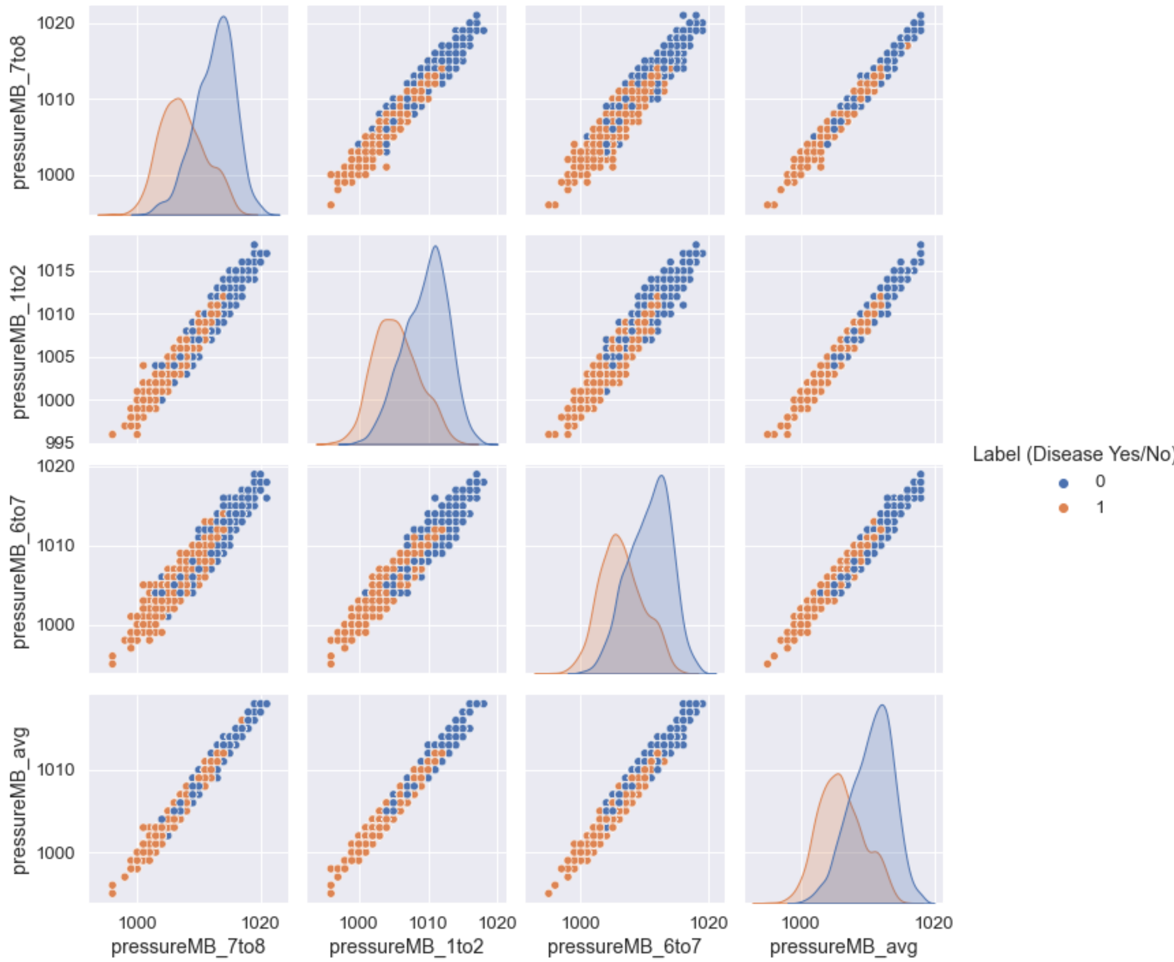
- The all windspeed columns are highly correlated with each other (> 50%)
- The correlation between windspeedKmph_avg(Km/h) & Label (Disease Yes/No) is 33.78% (+ve correlation)
- So, we can keep windspeedKmph_avg(Km/h)

Pairwise correlation in pressure

In [12]:
```
cols = ['pressureMB_7to8', 'pressureMB_1to2', 'pressureMB_6to7', 'pressureMB
hue_col = cols[-1]
get_Pairwise_Correlation(cols, hue_col)
```

	pressureMB_7to8	pressureMB_1to2	pressureMB_6to7	pressureMB_avg	Labe (Disease Yes/No)
pressureMB_7to8	1.000000	0.968658	0.963754	0.987808	-0.595491
pressureMB_1to2	0.968658	1.000000	0.958491	0.985832	-0.544604
pressureMB_6to7	0.963754	0.958491	1.000000	0.982979	-0.534666
pressureMB_avg	0.987808	0.985832	0.982979	1.000000	-0.562562
Label (Disease Yes/No)	-0.595491	-0.544604	-0.534666	-0.562562	1.000000

```
Pearson correlation between pressureMB_7to8 & Label (Disease Yes/No) is : -59.5
5%
Pearson correlation between pressureMB_1to2 & Label (Disease Yes/No) is : -54.4
6%
Pearson correlation between pressureMB_6to7 & Label (Disease Yes/No) is : -53.4
7%
Pearson correlation between pressureMB_avg & Label (Disease Yes/No) is : -56.2
6%
```



Observation:

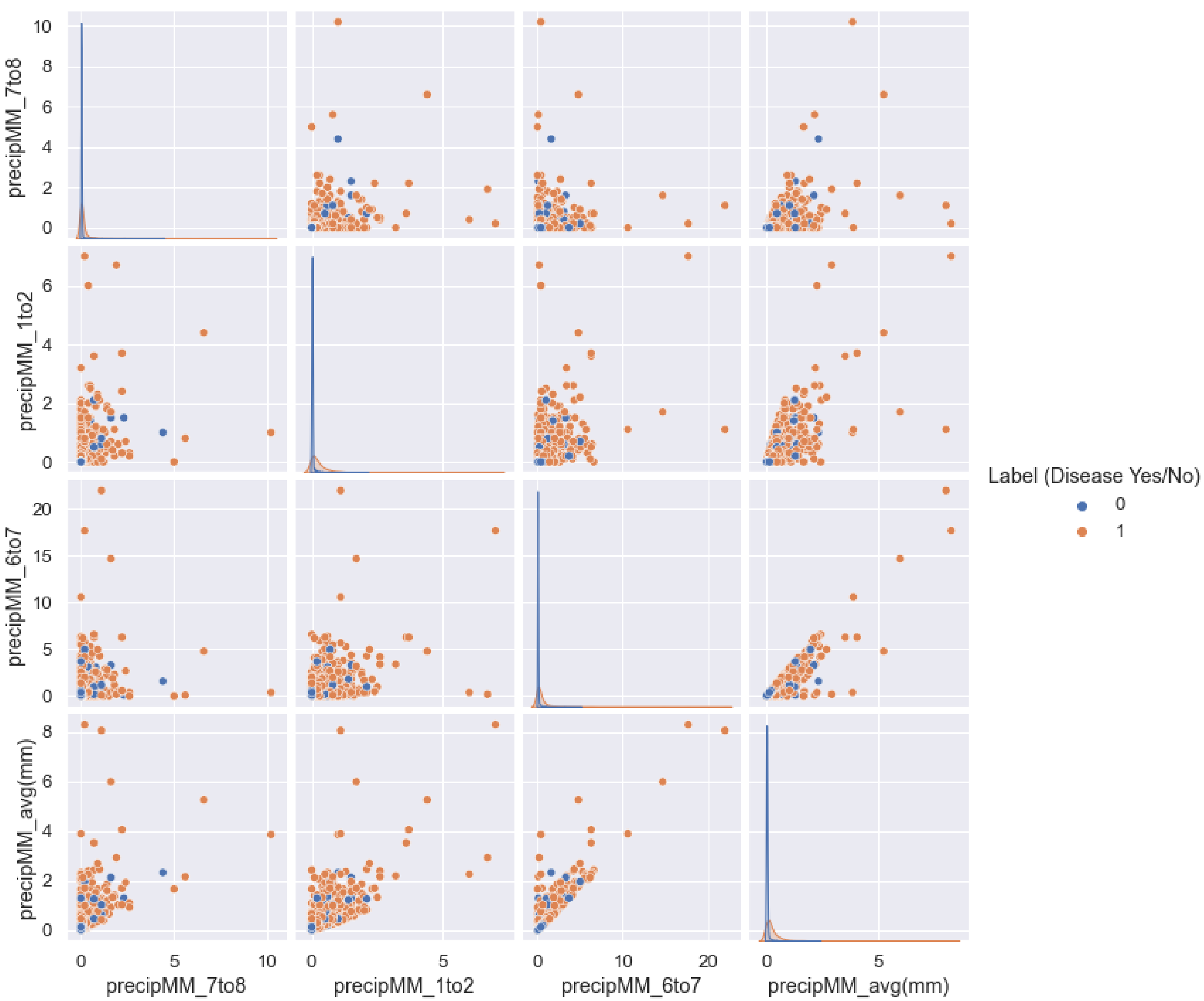
- The all windspeed columns are highly correlated with each other (> 50%)
- The correlation between pressureMB_7to8 & Label (Disease Yes/No) is -59.55% (-ve correlation)
- The correlation between pressureMB_avg & Label (Disease Yes/No) is -56.26% (-ve correlation)
- So, we can keep pressureMB_7to8 & pressureMB_avg

Pairwise correlation in precip

In [13]:
```
cols = ['precipMM_7to8', 'precipMM_1to2', 'precipMM_6to7', 'precipMM_avg(mm)
hue_col = cols[-1]
get_Pairwise_Correlation(cols, hue_col)
```

	precipMM_7to8	precipMM_1to2	precipMM_6to7	precipMM_avg(mm)	Label (Disease Yes/No)
precipMM_7to8	1.000000	0.353533	0.233664	0.527324	0.158429
precipMM_1to2	0.353533	1.000000	0.510297	0.750550	0.379157
precipMM_6to7	0.233664	0.510297	1.000000	0.912554	0.269750
precipMM_avg(mm)	0.527324	0.750550	0.912554	1.000000	0.344038
Label (Disease Yes/No)	0.158429	0.379157	0.269750	0.344038	1.000000

```
Pearson correlation between precipMM_7to8 & Label (Disease Yes/No) is : 15.84%
Pearson correlation between precipMM_1to2 & Label (Disease Yes/No) is : 37.92%
Pearson correlation between precipMM_6to7 & Label (Disease Yes/No) is : 26.97%
Pearson correlation between precipMM_avg(mm) & Label (Disease Yes/No) is : 34.
4%
```



Observation:

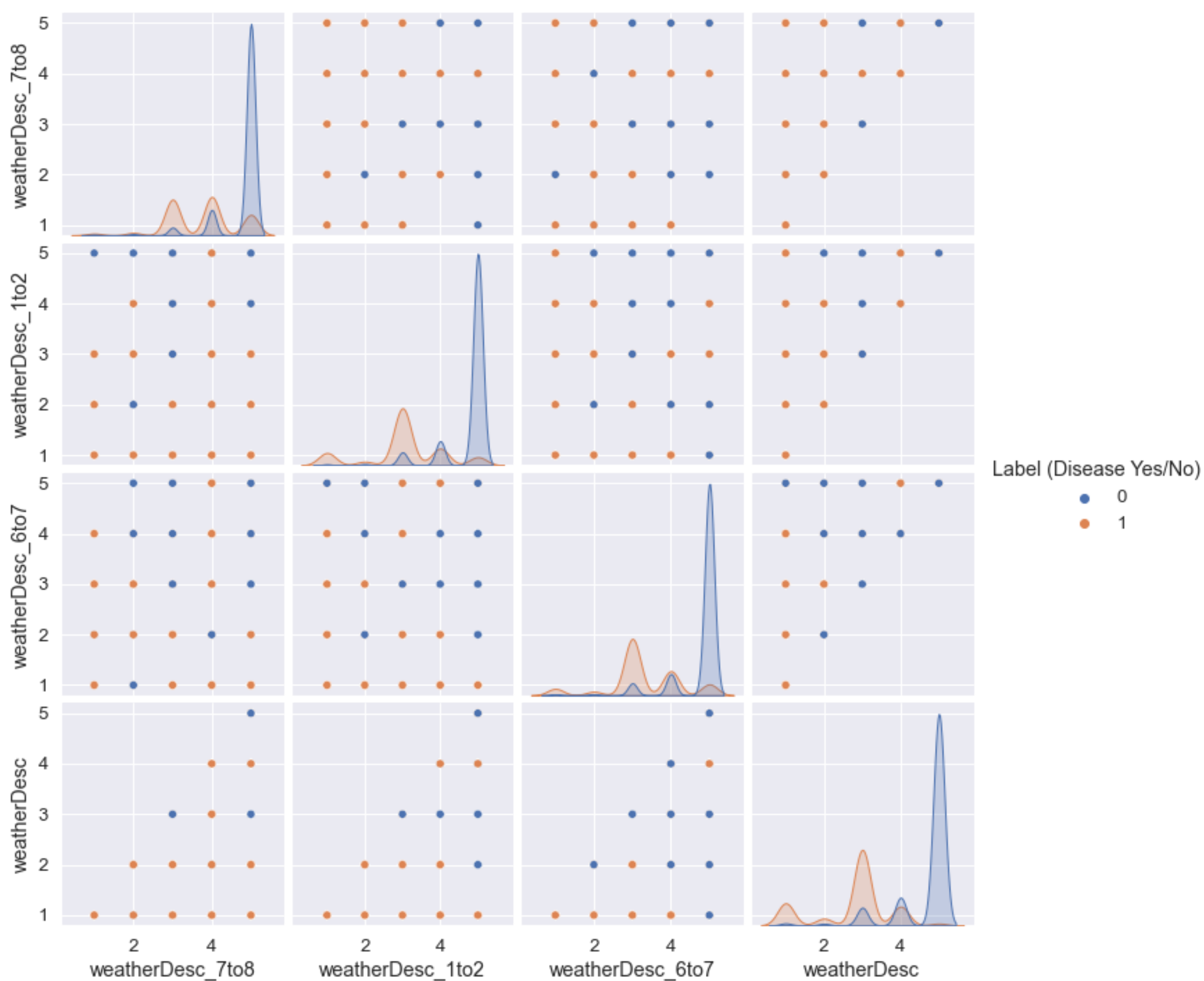
- The all precip columns are correlated with each other
- The correlation between precipMM_1to2 & Label (Disease Yes/No) is 37.92% (+ve correlation)
- The correlation between precipMM_avg(mm) & Label (Disease Yes/No) is 34.4% (+ve correlation)
- So, we can keep precipMM_1to2 & precipMM_avg(mm)

Pairwise correlation in weather

In [14]:
```
cols = ['weatherDesc_7to8', 'weatherDesc_1to2', 'weatherDesc_6to7', 'weather
hue_col = cols[-1]
get_Pairwise_Correlation(cols, hue_col)
```

	weatherDesc_7to8	weatherDesc_1to2	weatherDesc_6to7	weatherDesc	Label (Disease Yes/No)
weatherDesc_7to8	1.000000	0.706125	0.684671	0.734098	-0.605411
weatherDesc_1to2	0.706125	1.000000	0.763651	0.919745	-0.726626
weatherDesc_6to7	0.684671	0.763651	1.000000	0.875130	-0.701374
weatherDesc	0.734098	0.919745	0.875130	1.000000	-0.760430
Label (Disease Yes/No)	-0.605411	-0.726626	-0.701374	-0.760430	1.000000

```
Pearson correlation between weatherDesc_7to8 & Label (Disease Yes/No) is : -60.
54%
Pearson correlation between weatherDesc_1to2 & Label (Disease Yes/No) is : -72.
66%
Pearson correlation between weatherDesc_6to7 & Label (Disease Yes/No) is : -70.
14%
Pearson correlation between weatherDesc & Label (Disease Yes/No) is : -76.04%
```



Observation:

- The all weather columns are highly correlated with each other (> 50%)
- The correlation between weatherDesc & Label (Disease Yes/No) is -76.04% (-ve correlation)
- So, we can keep weatherDesc

Pairwise correlation with other

In [15]:
```
cols = ['Sunshine Hours', '%_soil_moisure', 'soil_pH', 'water_pH', 'water_TD
hue_col = cols[-1]
get_Pairwise_Correlation(cols, hue_col)
```

	Sunshine Hours	%_soil_moisure	soil_pH	water_pH	water_TDS_mgpl	Label (Disease Yes/No)
Sunshine Hours	1.000000	-0.769105	0.047175	0.053492	0.010106	-0.662051
%_soil_moisure	-0.769105	1.000000	-0.073358	-0.035720	0.001171	0.606175
soil_pH	0.047175	-0.073358	1.000000	-0.013978	-0.033262	-0.032147
water_pH	0.053492	-0.035720	-0.013978	1.000000	0.003156	-0.041087
water_TDS_mgpl	0.010106	0.001171	-0.033262	0.003156	1.000000	-0.006777
Label (Disease Yes/No)	-0.662051	0.606175	-0.032147	-0.041087	-0.006777	1.000000

```
Pearson correlation between Sunshine Hours & Label (Disease Yes/No) is : -66.2
1%
Pearson correlation between %_soil_moisure & Label (Disease Yes/No) is : 60.62%
Pearson correlation between soil_pH & Label (Disease Yes/No) is : -3.21%
Pearson correlation between water_pH & Label (Disease Yes/No) is : -4.11%
Pearson correlation between water_TDS_mgpl & Label (Disease Yes/No) is : -0.68%
```

Observation:

- The Sunshine Hours & %_soil_moisure shows the high correlation with Label (Disease Yes/No), -66.21% (-ve correlation) & 60.62% (+ve correlation) respectively
- The other show the correlation but very less
- So, we can keep Sunshine Hours & %_soil_moisure shows

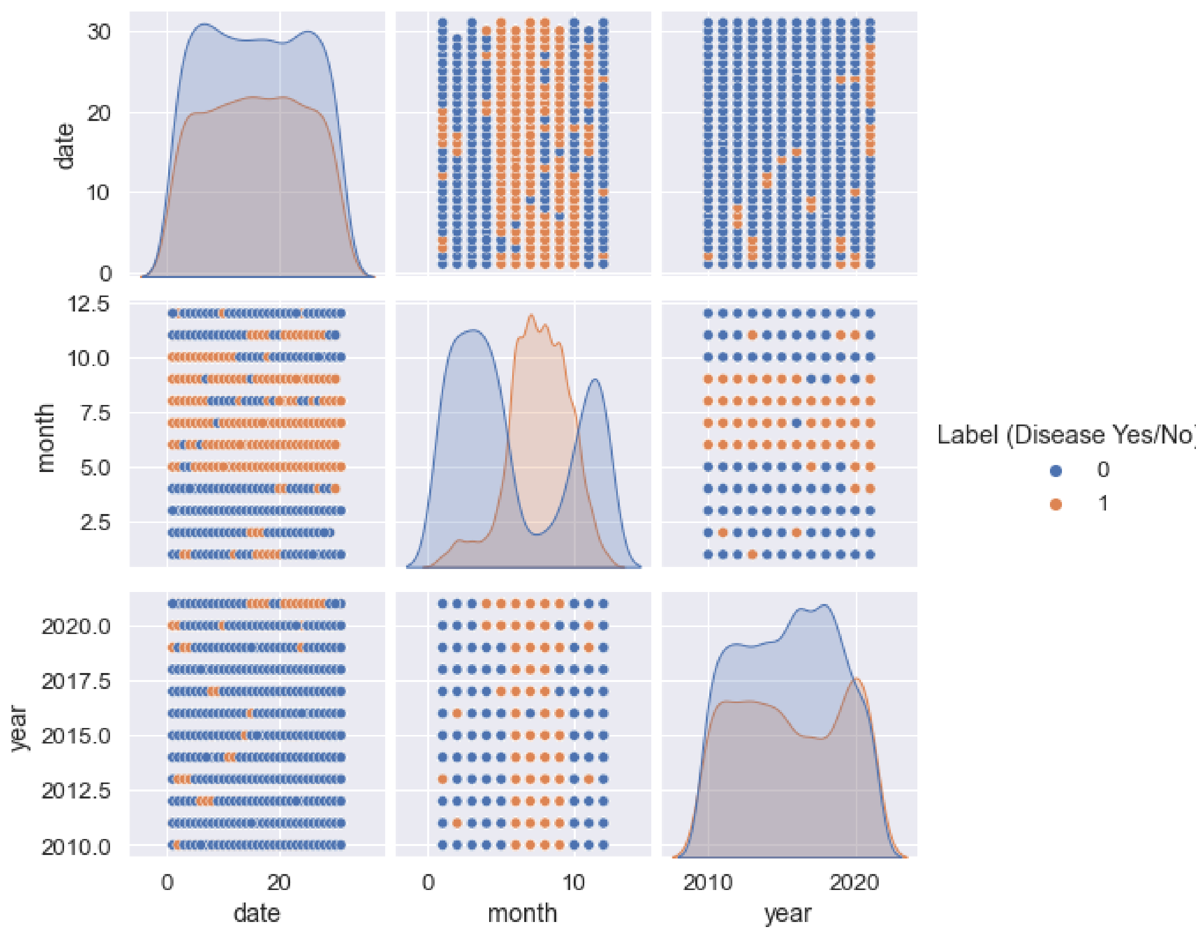
Pairwise correlation with dates

In [16]:

```
cols = ['date', 'month', 'year', 'Label (Disease Yes/No)']
hue_col = cols[-1]
get_Pairwise_Correlation(cols, hue_col)
```

	date	month	year	Label (Disease Yes/No)
date	1.000000	0.009698	-0.001954	-0.000855
month	0.009698	1.000000	-0.017837	0.256182
year	-0.001954	-0.017837	1.000000	0.009722
Label (Disease Yes/No)	-0.000855	0.256182	0.009722	1.000000

```
Pearson correlation between date & Label (Disease Yes/No) is : -0.09%
Pearson correlation between month & Label (Disease Yes/No) is : 25.62%
Pearson correlation between year & Label (Disease Yes/No) is : 0.97%
```



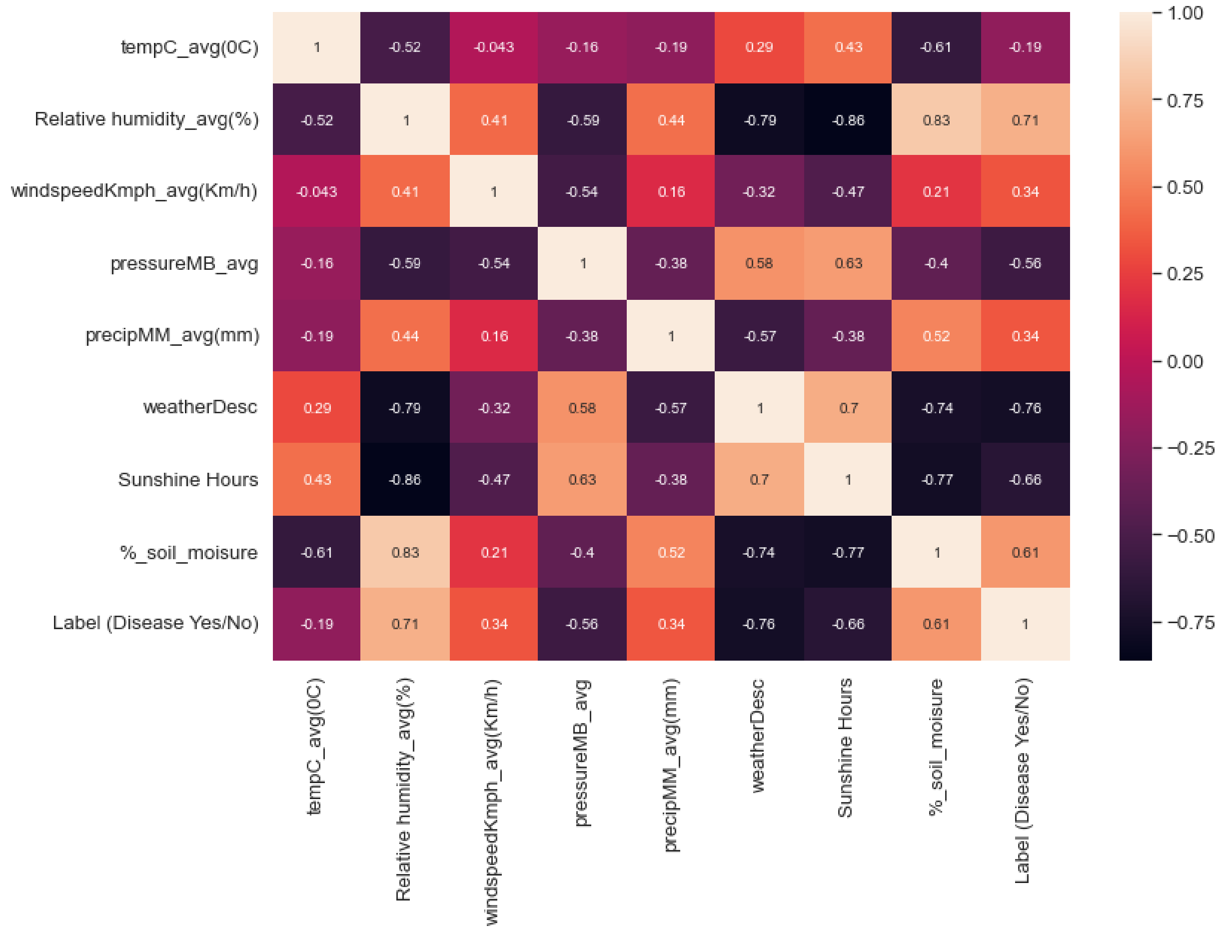
Observation:

- The month shows the correlation but < 50%
- So, we can think to keep it or not

In [17]:
```
df_with_correlation = df[['tempC_avg(0C)', 'Relative humidity_avg(%)', 'wind
                          'pressureMB_avg', 'precipMM_avg(mm)', 'weatherDesc
                          'Label (Disease Yes/No)']]
df_with_correlation.shape
```

Out[17]: (4227, 9)

In [18]:
```
fig_dims = (12, 8)
fig, ax = plt.subplots(figsize=fig_dims)
sns.heatmap(df_with_correlation.corr(), ax=ax, annot=True)
plt.show()
```



In [34]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import log_loss
from sklearn.metrics import cohen_kappa_score
from sklearn.metrics import confusion_matrix
from sklearn import metrics
import pickle
```

In [26]:
```
X, Y = df_with_correlation.iloc[:,:-1], df_with_correlation.iloc[:,-1]
X_train, X_test, y_train, y_test = train_test_split(X,Y, test_size = 0.3, ra
```

In [27]:
```
#Fitting Logistic Regression to the training set
from sklearn.linear_model import LogisticRegression

lr_Classifier= LogisticRegression(C=1.0, class_weight=None, dual=False, fit_
                   intercept_scaling=1, l1_ratio=None, max_iter=1000,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=3757, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
lr_Classifier.fit(X_train, y_train)
```

Out[27]:
```
LogisticRegression(max_iter=1000, random_state=3757)
```

In [28]:
```
y_pred = lr_Classifier.predict(X_test)
y_pred
```

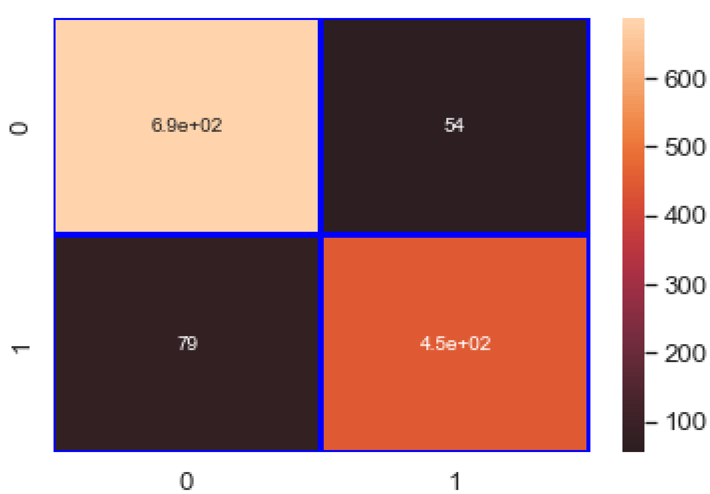
Out[28]:
```
array([1, 0, 1, ..., 0, 0, 1], dtype=int64)
```

In [32]:

```

print("Accuracy_score:", round((accuracy_score(y_test, y_pred))*100,2),'%')

print("Loss:", round((1-accuracy_score(y_test, y_pred))*100,2),'%')

print("Cohen_kappa_score:", round((cohen_kappa_score(y_test, y_pred))*100,2)

print("Classification_report:\n",metrics.classification_report(y_test, y_pre

# print("confusion_matrix:\n", confusion_matrix(y_test, y_pred))
print("confusion_matrix:\n", confusion_matrix(y_test, y_pred))


fig, ax = plt.subplots()
fig.set_size_inches(6,4) # WH
sns.heatmap(confusion_matrix(y_test, y_pred),
           annot=True,
                 linewidths = 2,
                linecolor = "blue",
                center=0)
```

```
Accuracy_score: 89.52 %
Loss: 10.48 %
Cohen_kappa_score: 78.27 %
Classification_report:
               precision    recall  f1-score   support

           0       0.90      0.93      0.91       742
           1       0.89      0.85      0.87       527

    accuracy                           0.90      1269
   macro avg       0.89      0.89      0.89      1269
weighted avg       0.90      0.90      0.89      1269

confusion_matrix:
 [[688  54]
 [ 79 448]]
```

Out[32]: <AxesSubplot:>



In [36]:

```
# save the model to disk
filename = 'lr_Classifier.pkl'
pickle.dump(lr_Classifier, open(filename, 'wb'))
```

In [ ]:

```

```

In [37]:

```
#Fitting K-NN classifier to the training set
from sklearn.neighbors import KNeighborsClassifier

knn_Classifier= KNeighborsClassifier(algorithm='auto', leaf_size=30, metric=
                     metric_params=None, n_jobs=-1, n_neighbors=5, p=2,
                     weights='uniform')
knn_Classifier.fit(X_train, y_train)
```

Out[37]: KNeighborsClassifier(n_jobs=-1)

In [38]:

```
y_pred = knn_Classifier.predict(X_test)
y_pred
```

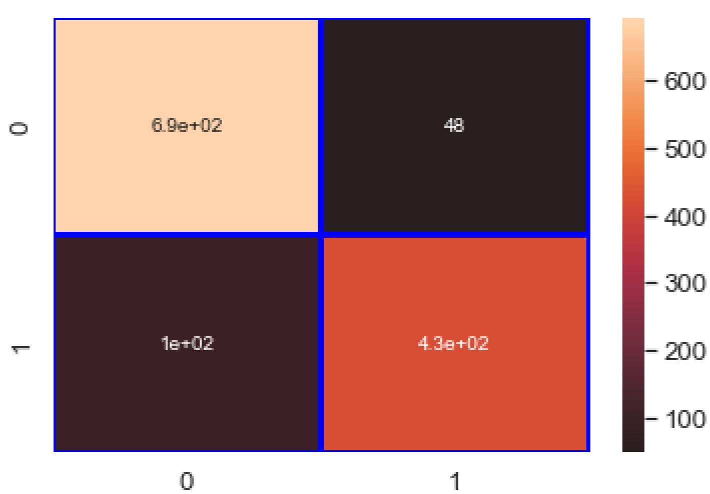
Out[38]: array([0, 0, 1, ..., 0, 0, 1], dtype=int64)

In [40]:

```

print("Accuracy_score:", round((accuracy_score(y_test, y_pred))*100,2),'%')

print("Loss:", round((1-accuracy_score(y_test, y_pred))*100,2),'%')

print("Cohen_kappa_score:", round((cohen_kappa_score(y_test, y_pred))*100,2)

print("Classification_report:\n",metrics.classification_report(y_test, y_pre

# print("confusion_matrix:\n", confusion_matrix(y_test, y_pred))
print("confusion_matrix:\n", confusion_matrix(y_test, y_pred))


fig, ax = plt.subplots()
fig.set_size_inches(6,4) # WH
sns.heatmap(confusion_matrix(y_test, y_pred),
           annot=True,
                 linewidths = 2,
                linecolor = "blue",
                center=0)
```

```
Accuracy_score: 88.26 %
Loss: 11.74 %
Cohen_kappa_score: 75.47 %
Classification_report:
               precision    recall  f1-score   support

           0       0.87      0.94      0.90       742
           1       0.90      0.81      0.85       527

    accuracy                           0.88      1269
   macro avg       0.89      0.87      0.88      1269
weighted avg       0.88      0.88      0.88      1269

confusion_matrix:
 [[694  48]
 [101 426]]
```

Out[40]: <AxesSubplot:>



In [41]:
```
# save the model to disk
filename = 'knn_Classifier_hc.pkl'
pickle.dump(knn_Classifier, open(filename, 'wb'))
```

In [ ]:
```

```

In [42]:
```
from sklearn.naive_bayes import GaussianNB

nb_Classifier = GaussianNB(priors=None, var_smoothing=1e-09)

nb_Classifier.fit(X_train, y_train)
```

Out[42]:
```
GaussianNB()
```

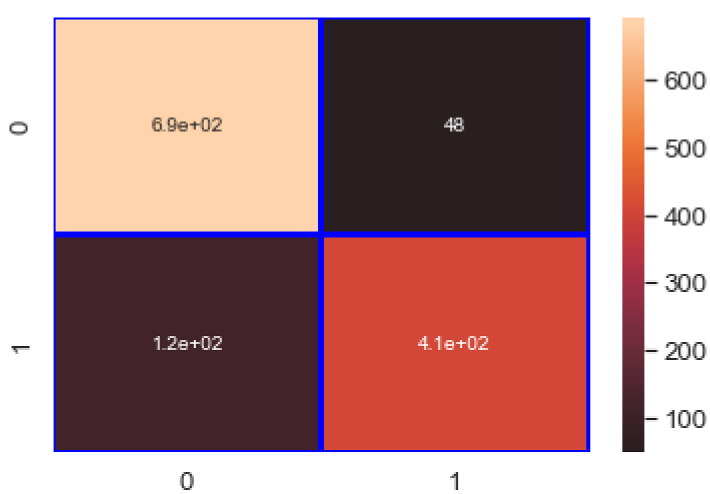
In [43]:
```
y_pred = nb_Classifier.predict(X_test)
y_pred
```

Out[43]:
```
array([1, 0, 1, ..., 0, 0, 1], dtype=int64)
```

In [44]:
```
print("Accuracy_score:", round((accuracy_score(y_test, y_pred))*100,2),'%')

print("Loss:", round((1-accuracy_score(y_test, y_pred))*100,2),'%')

print("Cohen_kappa_score:", round((cohen_kappa_score(y_test, y_pred))*100,2)

print("Classification_report:\n",metrics.classification_report(y_test, y_pre

# print("confusion_matrix:\n", confusion_matrix(y_test, y_pred))
print("confusion_matrix:\n", confusion_matrix(y_test, y_pred))


fig, ax = plt.subplots()
fig.set_size_inches(6,4) # WH
sns.heatmap(confusion_matrix(y_test, y_pred),
            annot=True,
                  linewidths = 2,
                 linecolor = "blue",
                 center=0)
```

```
Accuracy_score: 86.84 %
Loss: 13.16 %
Cohen_kappa_score: 72.36 %
Classification_report:
               precision    recall  f1-score   support

           0       0.85      0.94      0.89       742
           1       0.89      0.77      0.83       527

    accuracy                           0.87      1269
   macro avg       0.87      0.85      0.86      1269
weighted avg       0.87      0.87      0.87      1269

confusion_matrix:
 [[694  48]
 [119 408]]
```

Out[44]: <AxesSubplot:>



In [45]:
```
# save the model to disk
filename = 'nb_Classifier_hc.pkl'
pickle.dump(nb_Classifier, open(filename, 'wb'))
```

In [ ]:
```

```

In [47]:
```
from sklearn.tree import DecisionTreeClassifier

dt_Classifier = DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, cri
                       max_depth=None, max_features=None, max_leaf_nodes=Non
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0,
                       random_state=3757, splitter='best')

dt_Classifier.fit(X_train, y_train)
```

Out[47]:
```
DecisionTreeClassifier(random_state=3757)
```

In [48]:
```
y_pred = dt_Classifier.predict(X_test)
y_pred
```

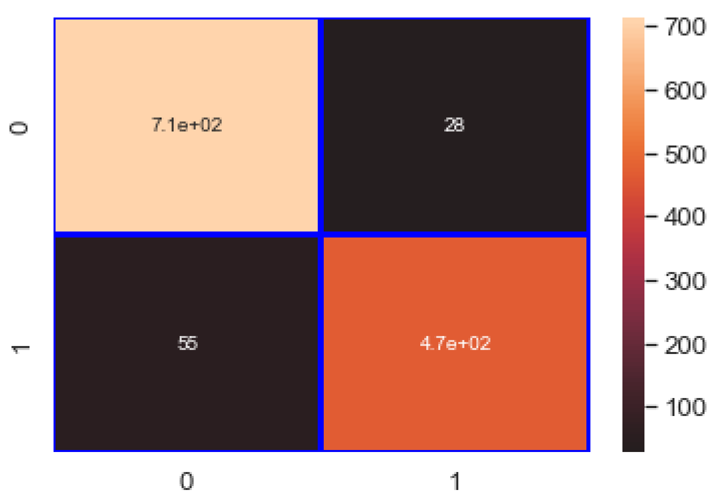
Out[48]:
```
array([1, 0, 1, ..., 0, 0, 1], dtype=int64)
```

In [49]:

```
print("Accuracy_score:", round((accuracy_score(y_test, y_pred))*100,2),'%')

print("Loss:", round((1-accuracy_score(y_test, y_pred))*100,2),'%')

print("Cohen_kappa_score:", round((cohen_kappa_score(y_test, y_pred))*100,2)

print("Classification_report:\n",metrics.classification_report(y_test, y_pre

# print("confusion_matrix:\n", confusion_matrix(y_test, y_pred))
print("confusion_matrix:\n", confusion_matrix(y_test, y_pred))


fig, ax = plt.subplots()
fig.set_size_inches(6,4) # WH
sns.heatmap(confusion_matrix(y_test, y_pred),
           annot=True,
                 linewidths = 2,
                linecolor = "blue",
                center=0)
```

```
Accuracy_score: 93.46 %
Loss: 6.54 %
Cohen_kappa_score: 86.43 %
Classification_report:
               precision    recall  f1-score   support

           0       0.93      0.96      0.95       742
           1       0.94      0.90      0.92       527

    accuracy                           0.93      1269
   macro avg       0.94      0.93      0.93      1269
weighted avg       0.93      0.93      0.93      1269

confusion_matrix:
 [[714  28]
 [ 55 472]]
```

Out[49]: <AxesSubplot:>



In [51]:
```
# save the model to disk
filename = 'dt_Classifier_hc.pkl'
pickle.dump(dt_Classifier, open(filename, 'wb'))
```

In [ ]:
```

```

In [52]:
```
from sklearn.ensemble import RandomForestClassifier

rf_Classifier = RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_
                        criterion='gini', max_depth=None, max_features='auto'
                        max_leaf_nodes=None, max_samples=None,
                        min_impurity_decrease=0.0, min_impurity_split=None,
                        min_samples_leaf=1, min_samples_split=2,
                        min_weight_fraction_leaf=0.0, n_estimators=100,
                        n_jobs=-1, oob_score=False, random_state=3757, verbos
                        warm_start=False)

rf_Classifier.fit(X_train, y_train)
```

Out[52]: RandomForestClassifier(n_jobs=-1, random_state=3757)

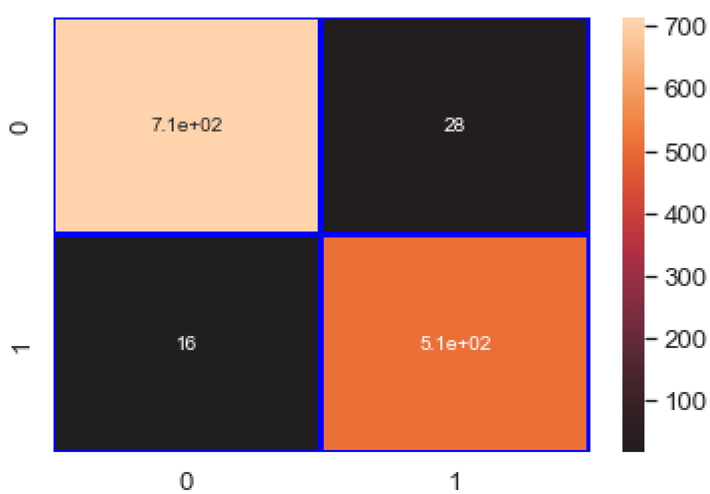
In [53]:
```
y_pred = rf_Classifier.predict(X_test)
y_pred
```

Out[53]: array([1, 0, 1, ..., 0, 0, 1], dtype=int64)

In [54]:
```
print("Accuracy_score:", round((accuracy_score(y_test, y_pred))*100,2),'%')

print("Loss:", round((1-accuracy_score(y_test, y_pred))*100,2),'%')

print("Cohen_kappa_score:", round((cohen_kappa_score(y_test, y_pred))*100,2)

print("Classification_report:\n",metrics.classification_report(y_test, y_pre

# print("confusion_matrix:\n", confusion_matrix(y_test, y_pred))
print("confusion_matrix:\n", confusion_matrix(y_test, y_pred))


fig, ax = plt.subplots()
fig.set_size_inches(6,4) # WH
sns.heatmap(confusion_matrix(y_test, y_pred),
           annot=True,
                 linewidths = 2,
                linecolor = "blue",
                center=0)
```

```
Accuracy_score: 96.53 %
Loss: 3.47 %
Cohen_kappa_score: 92.88 %
Classification_report:
               precision    recall  f1-score   support

           0       0.98      0.96      0.97       742
           1       0.95      0.97      0.96       527

    accuracy                           0.97      1269
   macro avg       0.96      0.97      0.96      1269
weighted avg       0.97      0.97      0.97      1269

confusion_matrix:
 [[714  28]
 [ 16 511]]
```

Out[54]: <AxesSubplot:>



In [55]:

```
# save the model to disk
filename = 'rf_Classifier_hc.pkl'
pickle.dump(rf_Classifier, open(filename, 'wb'))
```

In [ ]:

```

```