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In [1]:
```
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix,classification_report,f1_score
from imblearn.over_sampling import RandomOverSampler, SMOTE

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Helper class to perform fitting data along with cross validation of hyperparameters for
# 'SVC','Logistic Regression','Decision Tree Classifier' classifiers.

class Predictors:
    def __init__(self):
        self.models = []
        self.models_names = ['SVC','Logistic Regression','Decision Tree Classifier']
        parameters = {'kernel':('linear', 'rbf', 'sigmoid'), 'C':[0.01,1, 10, 100,1000]}
        svc = SVC()
        self.models.append(GridSearchCV(svc, parameters,n_jobs=-1))

        parameters = {
            'C': [0.0001,0.001,0.01, 0.1],
            'penalty': ['l1', 'l2'],
            'solver': ['liblinear', 'saga'],
            'max_iter': [100, 200]
        }
        log = LogisticRegression(random_state=42)
        self.models.append(GridSearchCV(log, parameters,n_jobs=-1))

        parameters = {
            'max_depth': [3, 5, 10, 15, 20],
```

```
            'min_samples_leaf': [1, 2, 4, 6, 8],
        }
        DT = DecisionTreeClassifier(random_state=42)
        self.models.append(GridSearchCV(DT, parameters,n_jobs=-1))

    def fit(self,X,y,sample_weight=None):
        for model in self.models:
            model.fit(X,y,sample_weight = sample_weight)

    def predict(self,X_test,y_test):
        for i in range(len(self.models)):
            model = self.models[i]
            name = self.models_names[i]
            print('For model ' +str(name)+' following are the best parametrs ' + str(model.best_params_))
            y_pred = model.predict(X_test)
            y_pred = model.best_estimator_.predict(X_test)
            cf_matrix = confusion_matrix(y_test, y_pred)
            print(classification_report(y_test,y_pred))
            accuracy_validation = '{}'.format(f1_score(y_test,y_pred,average='macro'))
            print("Macro F1 score of the model on test dataset turns out to be " +accuracy_validation)
            fig, ax = plt.subplots(figsize=(4,4))
            s = sns.heatmap(cf_matrix/np.sum(cf_matrix), annot=True, fmt='.2%', cmap='Blues',ax=ax)
            s.set(xlabel='Predicted Label', ylabel='True Label',title='Model = '+str(name))
            plt.plot()
```

In [3]:
```
# Data processing
data = pd.read_csv('aps_failure_training_set.csv')
data = data.replace('na',np.NaN)
data[data.columns[0]].replace({'neg':'0','pos':'1'},inplace=True)
data[data.columns[0]] = data[data.columns[0]].astype(float)
data[data.columns[1:]] = data[data.columns[1:]].astype(float)
data.dropna(inplace=True)
```

In [4]:
```
data.head()
```

Out[4]:

	class	aa_000	ab_000	ac_000	ad_000	ae_000	af_000	ag_000	ag_001	ag_002	...	ee_002	ee_003	ee_004	ee_005
16	0.0	31300.0	0.0	784.0	740.0	0.0	0.0	0.0	0.0	0.0	...	798872.0	112724.0	51736.0	7054.0
179	0.0	97000.0	0.0	378.0	160.0	0.0	0.0	0.0	0.0	0.0	...	1078982.0	313334.0	511330.0	552328.0
225	0.0	124656.0	2.0	278.0	170.0	0.0	0.0	0.0	0.0	0.0	...	1205696.0	866148.0	697610.0	700400.0
394	1.0	281324.0	2.0	3762.0	2346.0	0.0	0.0	4808.0	215720.0	967572.0	...	624606.0	269976.0	638838.0	1358354.0
413	1.0	43482.0	0.0	1534.0	1388.0	0.0	0.0	0.0	0.0	40024.0	...	497196.0	121166.0	202272.0	232636.0

5 rows × 171 columns

In [5]:

```
# Creating and splitting data
y = data[data.columns[0]]
X = data[data.columns[1:]]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15, random_state=42)
```

In [6]:

```
parameters = {'kernel':('linear', 'rbf', 'sigmoid'), 'C':[1e2,1e3,1e4]}
svc = SVC()
clf_svc = GridSearchCV(svc, parameters,n_jobs=-1)
clf_svc.fit(X_train,y_train)
```

Out[6]:

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

In [7]:

```
print(clf_svc.best_params_)
```

```
{'C': 1000.0, 'kernel': 'rbf'}
```

In [8]:

```
parameters = {
    'C': [0.0001,0.001,0.01],
    'penalty': ['l1', 'l2'],
    'solver': ['liblinear', 'saga'],
```

```
    'max_iter': [100, 200]
}
log = LogisticRegression(random_state=42)
clf_log = GridSearchCV(log, parameters,n_jobs=-1)
clf_log.fit(X_train,y_train)
```

Out[8]:

```
▸ GridSearchCV
▸ estimator: LogisticRegression
    ▸ LogisticRegression
```

In [9]:

```
print(clf_log.best_params_)
```

```
{'C': 0.01, 'max_iter': 100, 'penalty': 'l1', 'solver': 'liblinear'}
```

In [10]:

```
parameters = {
    'max_depth': [3, 5, 10, 15, 20],
    'min_samples_leaf': [1, 2, 4, 6, 8],
}

DT = DecisionTreeClassifier(random_state=42)
clf_dt = GridSearchCV(DT, parameters,n_jobs=-1)
clf_dt.fit(X_train,y_train)
```

Out[10]:

```
▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
    ▸ DecisionTreeClassifier
```

In [11]:

```
print(clf_dt.best_params_)
```

```
{'max_depth': 10, 'min_samples_leaf': 1}
```

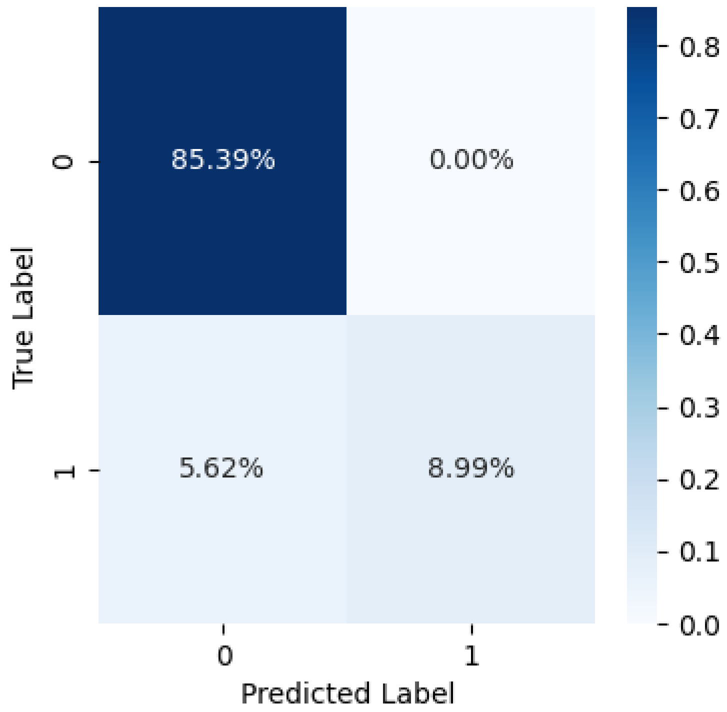
In [12]:

```
y_pred_svc = clf_svc.best_estimator_.predict(X_test)
cf_matrix = confusion_matrix(y_test, y_pred_svc)
print(classification_report(y_test,y_pred_svc))
accuracy_validation = '{}'.format(f1_score(y_test,y_pred_svc,average='macro'))
```

```
print("Macro F1 score of the SVC on test dataset turns out to be " +accuracy_validation)
fig, ax = plt.subplots(figsize=(4,4))
s = sns.heatmap(cf_matrix/np.sum(cf_matrix), annot=True, fmt='.2%', cmap='Blues',ax=ax)
s.set(xlabel='Predicted Label', ylabel='True Label')
```

```
              precision    recall  f1-score   support

         0.0       0.94      1.00      0.97        76
         1.0       1.00      0.62      0.76        13

    accuracy                           0.94        89
   macro avg       0.97      0.81      0.87        89
weighted avg       0.95      0.94      0.94        89

Macro F1 score of the SVC on test dataset turns out to be 0.8650288140734002
```

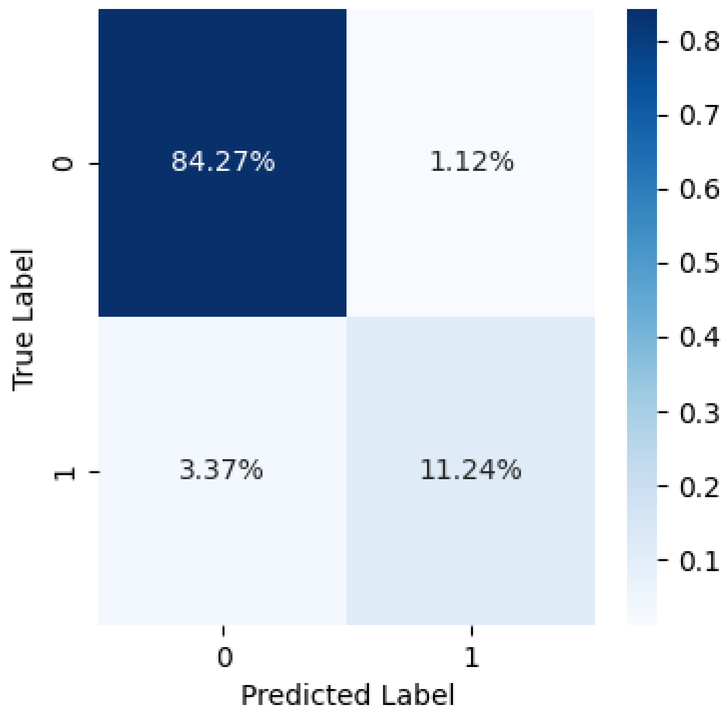
Out[12]:
```
[Text(0.5, 14.722222222222216, 'Predicted Label'),
 Text(20.72222222222222, 0.5, 'True Label')]
```



In [13]:
```python
y_pred_log = clf_log.best_estimator_.predict(X_test)
cf_matrix = confusion_matrix(y_test, y_pred_log)
print(classification_report(y_test,y_pred_log))
accuracy_validation = '{}'.format(f1_score(y_test,y_pred_log,average='macro'))
print("Macro F1 score of the LogReg on test dataset turns out to be " +accuracy_validation)
fig, ax = plt.subplots(figsize=(4,4))
s = sns.heatmap(cf_matrix/np.sum(cf_matrix), annot=True, fmt='.2%', cmap='Blues',ax=ax)
s.set(xlabel='Predicted Label', ylabel='True Label')
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.99      0.97        76
         1.0       0.91      0.77      0.83        13

    accuracy                           0.96        89
   macro avg       0.94      0.88      0.90        89
weighted avg       0.95      0.96      0.95        89

Macro F1 score of the LogReg on test dataset turns out to be 0.9036796536796536
```

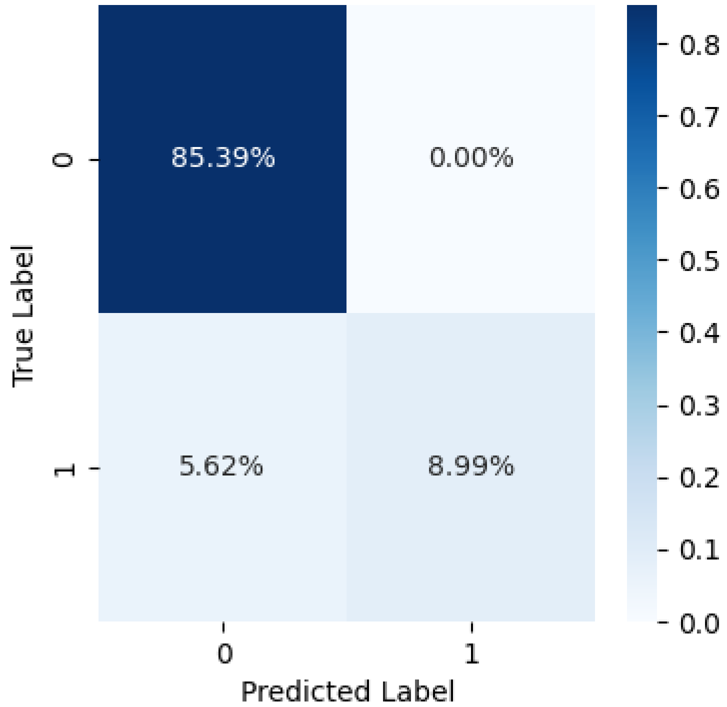
Out[13]:
```
[Text(0.5, 14.722222222222216, 'Predicted Label'),
 Text(20.72222222222222, 0.5, 'True Label')]
```



In [14]:
```
y_pred_dt = clf_dt.best_estimator_.predict(X_test)
cf_matrix = confusion_matrix(y_test, y_pred_dt)
print(classification_report(y_test,y_pred_dt))
accuracy_validation = '{}'.format(f1_score(y_test,y_pred_dt,average='macro'))
print("Macro F1 score of the Decision Trees on test dataset turns out to be " +accuracy_validation)
fig, ax = plt.subplots(figsize=(4,4))
s = sns.heatmap(cf_matrix/np.sum(cf_matrix), annot=True, fmt='.2%', cmap='Blues',ax=ax)
s.set(xlabel='Predicted Label', ylabel='True Label')
```

```
              precision    recall  f1-score   support

         0.0       0.94      1.00      0.97        76
         1.0       1.00      0.62      0.76        13

    accuracy                           0.94        89
   macro avg       0.97      0.81      0.87        89
weighted avg       0.95      0.94      0.94        89

Macro F1 score of the Decision Trees on test dataset turns out to be 0.8650288140734002
```

Out[14]:
```
[Text(0.5, 14.722222222222216, 'Predicted Label'),
 Text(20.72222222222222, 0.5, 'True Label')]
```



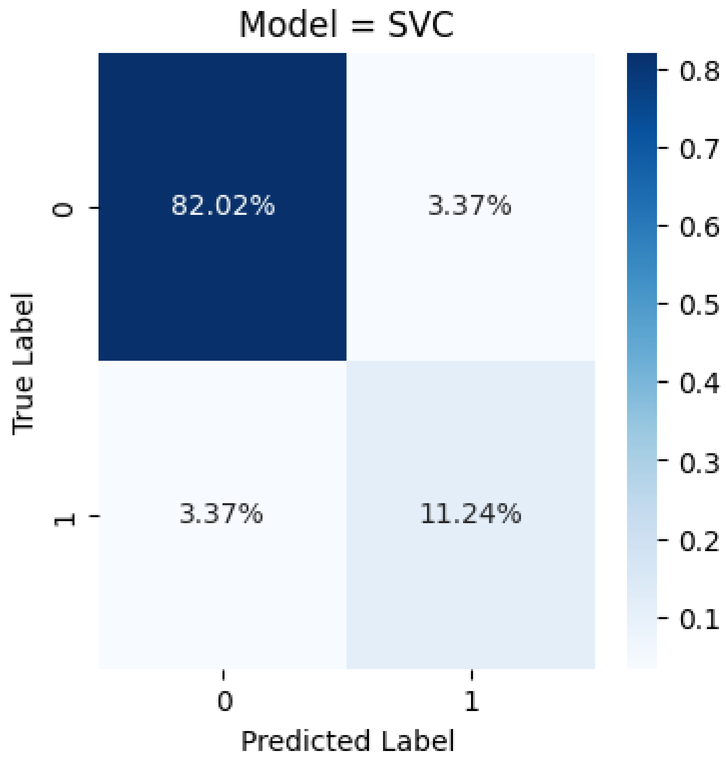
Task 2

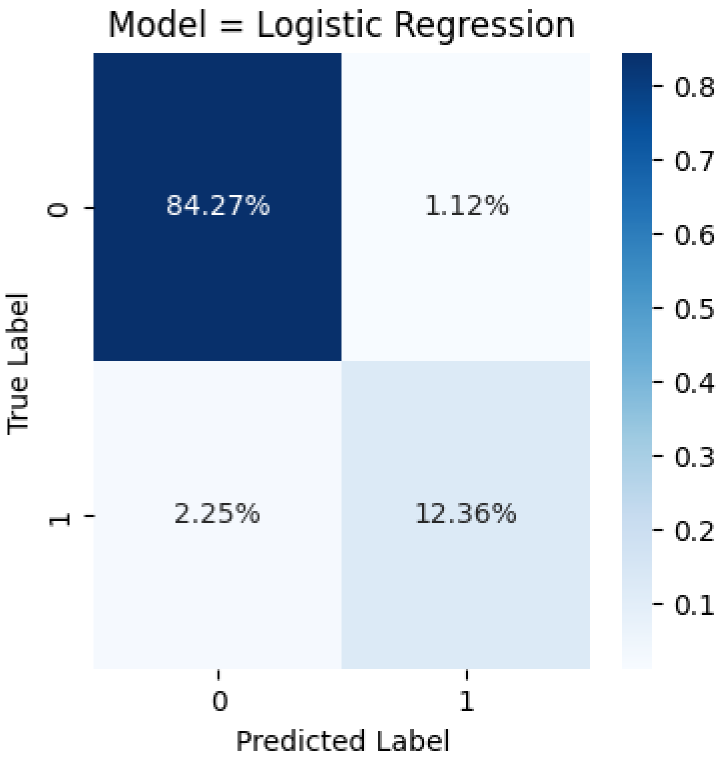
In [15]:
```
# Task A
# using random sampler to carry out sampling
```

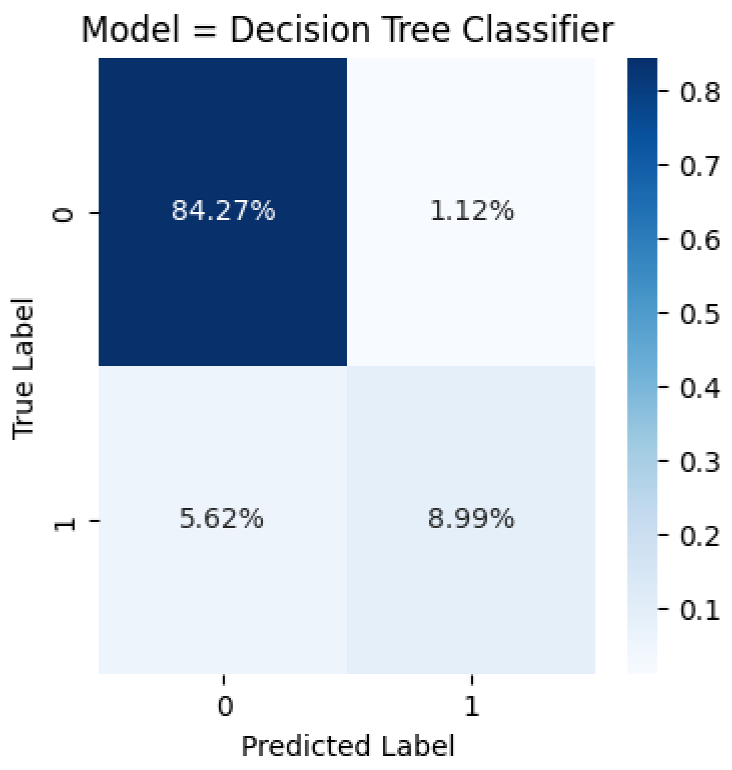
```python
predictor_ROS = Predictors()
ros = RandomOverSampler(random_state=42)
X_ros, y_ros = ros.fit_resample(X_train, y_train)
predictor_ROS.fit(X_ros,y_ros)
```

In [16]:
```python
predictor_ROS.predict(X_test,y_test)
```

```
For model SVC following are the best parametrs {'C': 0.01, 'kernel': 'linear'}
              precision    recall  f1-score   support

         0.0       0.96      0.96      0.96        76
         1.0       0.77      0.77      0.77        13

    accuracy                           0.93        89
   macro avg       0.86      0.86      0.86        89
weighted avg       0.93      0.93      0.93        89

Macro F1 score of the model on test dataset turns out to be 0.8648785425101215
For model Logistic Regression following are the best parametrs {'C': 0.001, 'max_iter': 100, 'penalty': 'l1', 'solver': 'liblin
ear'}
              precision    recall  f1-score   support

         0.0       0.97      0.99      0.98        76
         1.0       0.92      0.85      0.88        13

    accuracy                           0.97        89
   macro avg       0.95      0.92      0.93        89
weighted avg       0.97      0.97      0.97        89

Macro F1 score of the model on test dataset turns out to be 0.9301960784313725
For model Decision Tree Classifier following are the best parametrs {'max_depth': 15, 'min_samples_leaf': 1}
              precision    recall  f1-score   support

         0.0       0.94      0.99      0.96        76
         1.0       0.89      0.62      0.73        13

    accuracy                           0.93        89
   macro avg       0.91      0.80      0.84        89
weighted avg       0.93      0.93      0.93        89

Macro F1 score of the model on test dataset turns out to be 0.8444055944055944
```


Model = SVC
82.02%
3.37%
3.37%
11.24%
True Label
Predicted Label
0
1
0
1
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1

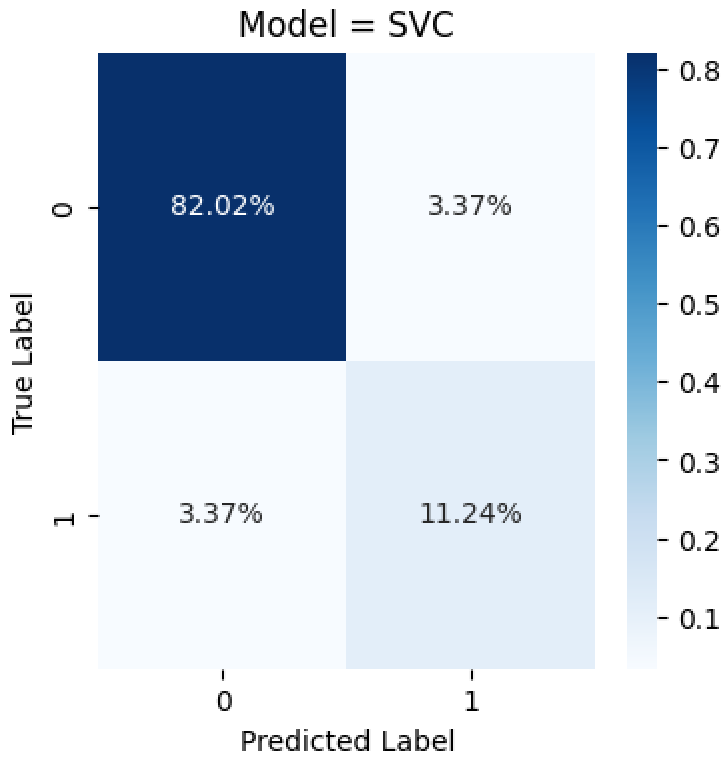

Model = Logistic Regression
84.27%
1.12%
2.25%
12.36%
True Label
0
1
0
1
Predicted Label
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1

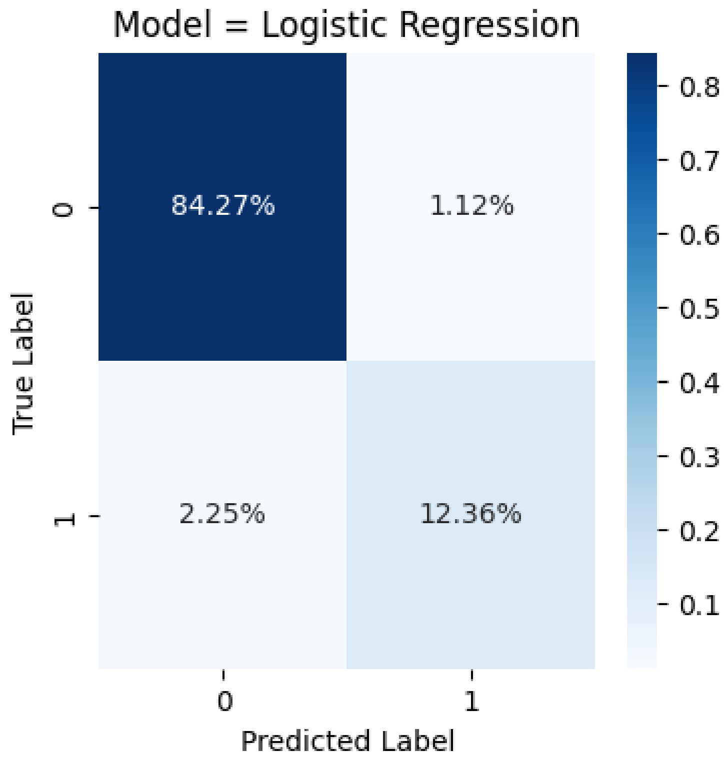


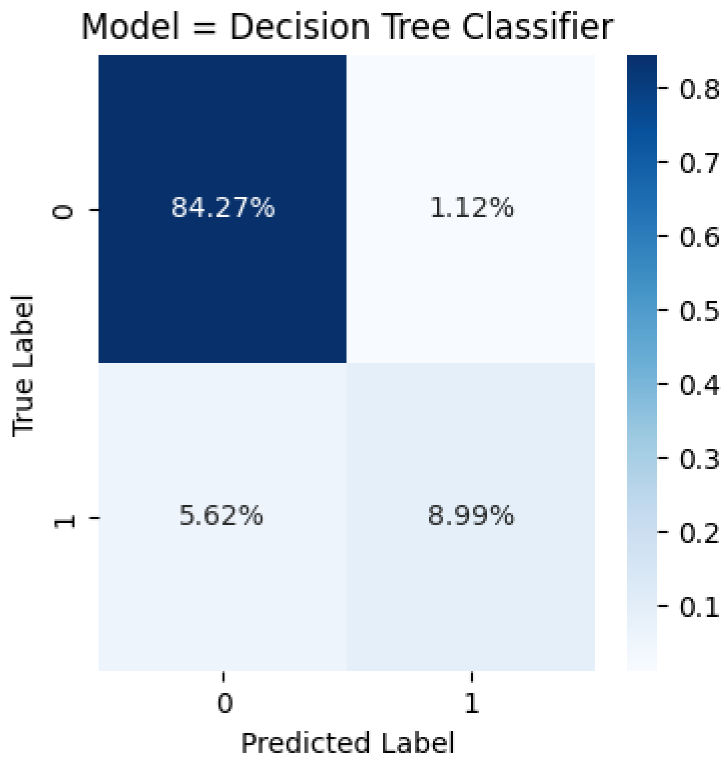
In [17]:

```
# Task B
# using class_weights carry out sampling

# Assigning class weights
P = np.where(y_train == 0,(1/np.sum(y_train == 0)),(1/np.sum(y_train == 1)))
P = P / np.sum(P)
#Sampling from the X_Train and y_train depending upon class weights
samples = np.random.choice(np.arange(0, len(X_train)), p=P,size=len(X_train))
predictor_class_weight = Predictors()
X_class_weight = X_train.iloc[samples]
y_class_weight = y_train.iloc[samples]
predictor_class_weight.fit(X_ros,y_ros)
predictor_class_weight.predict(X_test,y_test)
```

```
For model SVC following are the best parametrs {'C': 0.01, 'kernel': 'linear'}
              precision    recall  f1-score   support

         0.0       0.96      0.96      0.96        76
         1.0       0.77      0.77      0.77        13

    accuracy                           0.93        89
   macro avg       0.86      0.86      0.86        89
weighted avg       0.93      0.93      0.93        89

Macro F1 score of the model on test dataset turns out to be 0.8648785425101215
For model Logistic Regression following are the best parametrs {'C': 0.001, 'max_iter': 100, 'penalty': 'l1', 'solver': 'liblin
ear'}
              precision    recall  f1-score   support

         0.0       0.97      0.99      0.98        76
         1.0       0.92      0.85      0.88        13

    accuracy                           0.97        89
   macro avg       0.95      0.92      0.93        89
weighted avg       0.97      0.97      0.97        89

Macro F1 score of the model on test dataset turns out to be 0.9301960784313725
For model Decision Tree Classifier following are the best parametrs {'max_depth': 15, 'min_samples_leaf': 1}
              precision    recall  f1-score   support

         0.0       0.94      0.99      0.96        76
         1.0       0.89      0.62      0.73        13

    accuracy                           0.93        89
   macro avg       0.91      0.80      0.84        89
weighted avg       0.93      0.93      0.93        89

Macro F1 score of the model on test dataset turns out to be 0.8444055944055944
```

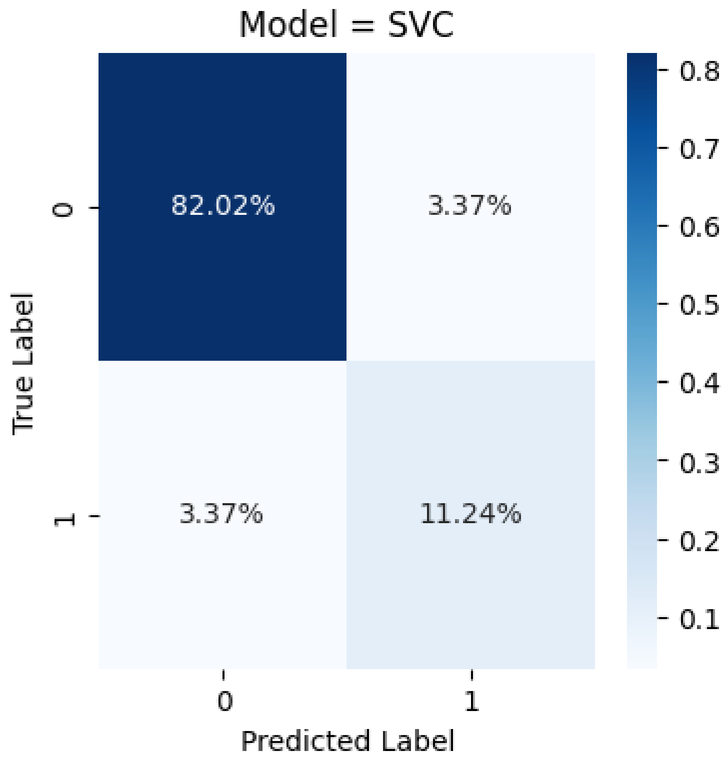

Model = SVC
82.02%
3.37%
3.37%
11.24%
True Label
Predicted Label
0
1
0
1
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1

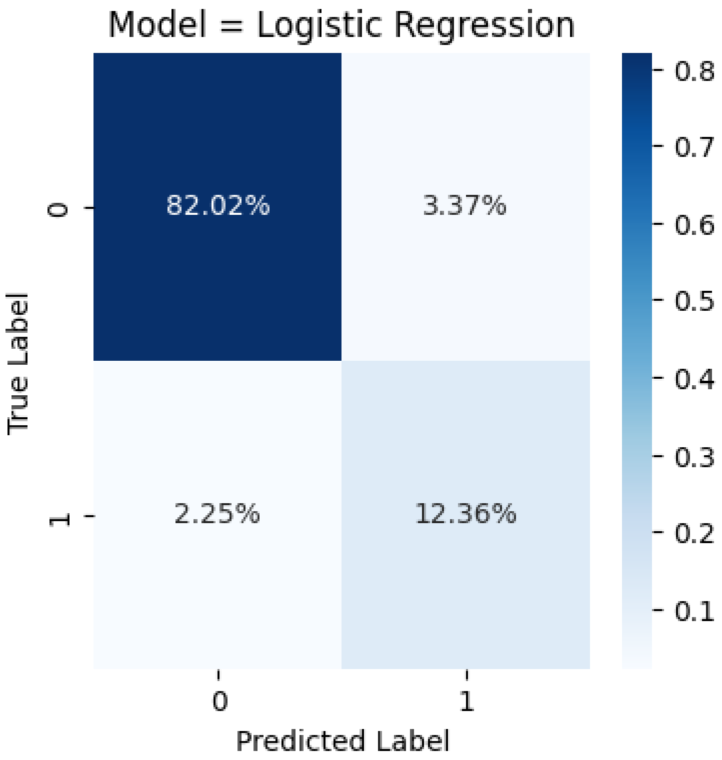

Model = Logistic Regression
84.27%
1.12%
2.25%
12.36%
True Label
Predicted Label
0
1
0
1
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1

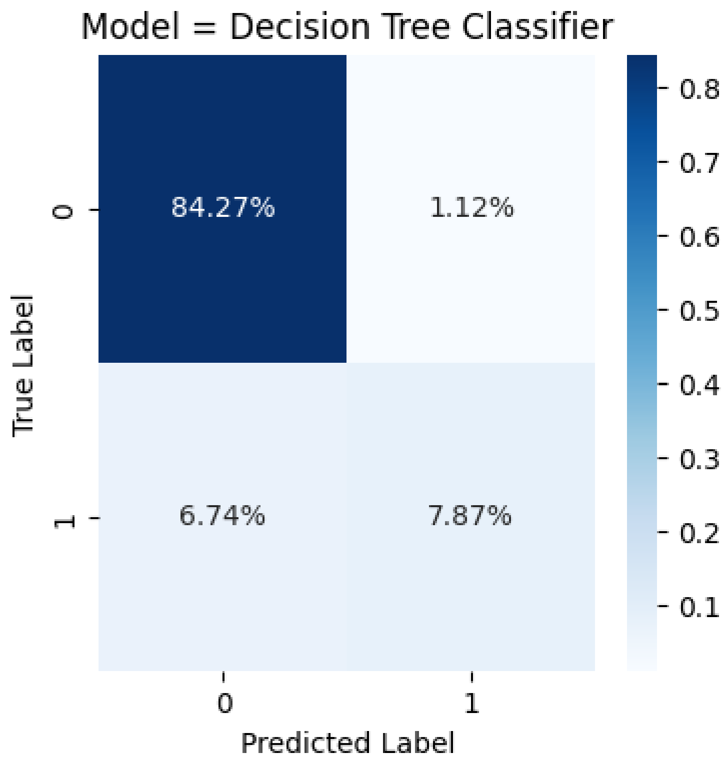


In [18]:
```
# Task C
# using sample_weights carry out sampling
predictor_sample_weight = Predictors()
predictor_sample_weight.fit(X_train,y_train,sample_weight=P)
predictor_sample_weight.predict(X_test,y_test)
```

```
For model SVC following are the best parametrs {'C': 0.01, 'kernel': 'linear'}
              precision    recall  f1-score   support

         0.0       0.96      0.96      0.96        76
         1.0       0.77      0.77      0.77        13

    accuracy                           0.93        89
   macro avg       0.86      0.86      0.86        89
weighted avg       0.93      0.93      0.93        89

Macro F1 score of the model on test dataset turns out to be 0.8648785425101215
For model Logistic Regression following are the best parametrs {'C': 0.001, 'max_iter': 100, 'penalty': 'l1', 'solver': 'liblin
ear'}
              precision    recall  f1-score   support

         0.0       0.97      0.96      0.97        76
         1.0       0.79      0.85      0.81        13

    accuracy                           0.94        89
   macro avg       0.88      0.90      0.89        89
weighted avg       0.95      0.94      0.94        89

Macro F1 score of the model on test dataset turns out to be 0.890851116016679
For model Decision Tree Classifier following are the best parametrs {'max_depth': 15, 'min_samples_leaf': 1}
              precision    recall  f1-score   support

         0.0       0.93      0.99      0.96        76
         1.0       0.88      0.54      0.67        13

    accuracy                           0.92        89
   macro avg       0.90      0.76      0.81        89
weighted avg       0.92      0.92      0.91        89

Macro F1 score of the model on test dataset turns out to be 0.8110403397027601
```


Model = SVC
82.02%
3.37%
3.37%
11.24%
True Label
Predicted Label
0
1
0
1
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1


Model = Logistic Regression
82.02%
3.37%
2.25%
12.36%
True Label
Predicted Label
0
1
0
1
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1



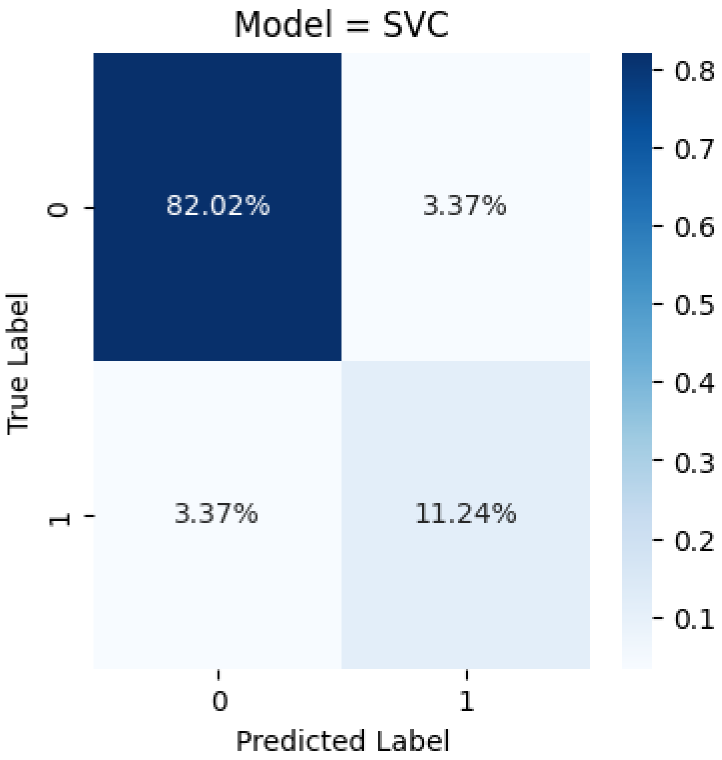
SMOTE : Synthetic Minority Over-sampling Technique:
Generates synthetic samples for the minority class to balance the class distribution by selecting a random number of k-nearest neighbors (typically k=5) from the minority class. These neighbors are close in feature space to the current minority class sample. Following steps are performed by SMOTE:

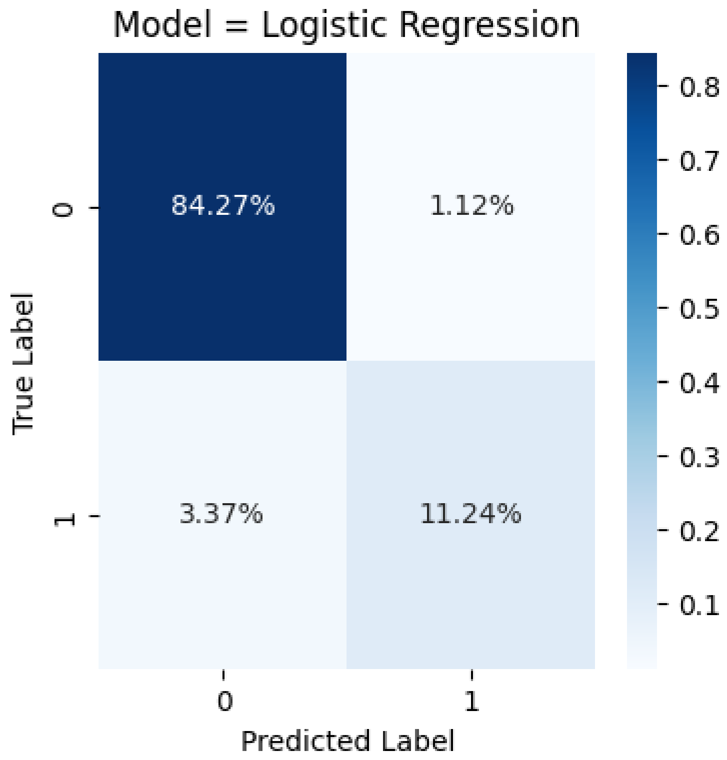
- For each minority sample, SMOTE selects one or more of its nearest neighbors.
- It then generates a synthetic data point along the line segment joining the minority sample and its neighbor.
- This process is repeated for many minority class

In [19]:
```
# Task D
# creative ideas to address the class imbalance via using SMOTE
sm = SMOTE(random_state=42)
X_smote, y_smote = sm.fit_resample(X_train, y_train)
predictor_smote = Predictors()
```

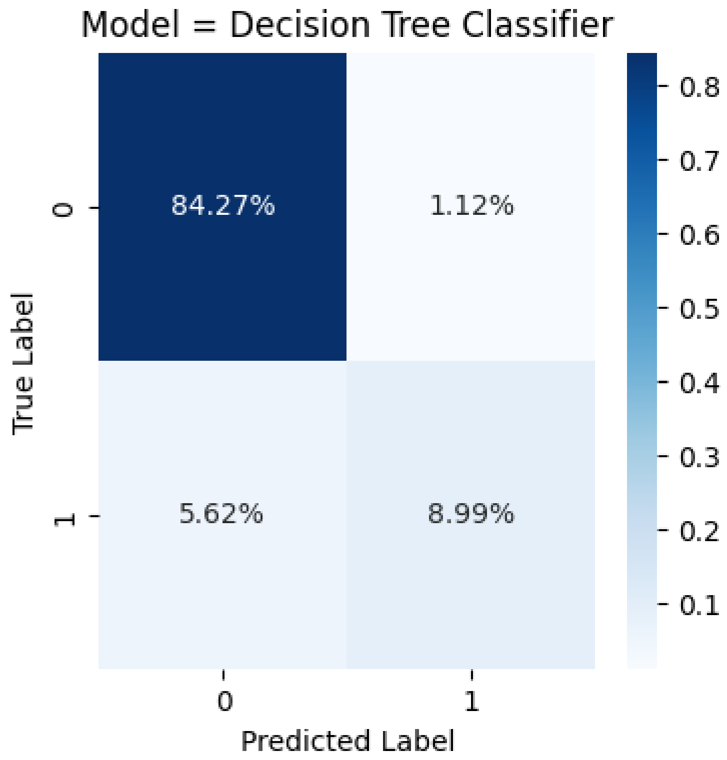
```
predictor_smote.fit(X_smote,y_smote)
predictor_smote.predict(X_test,y_test)
```

```
For model SVC following are the best parametrs {'C': 0.01, 'kernel': 'linear'}
              precision    recall  f1-score   support

         0.0       0.96      0.96      0.96        76
         1.0       0.77      0.77      0.77        13

    accuracy                           0.93        89
   macro avg       0.86      0.86      0.86        89
weighted avg       0.93      0.93      0.93        89

Macro F1 score of the model on test dataset turns out to be 0.8648785425101215
For model Logistic Regression following are the best parametrs {'C': 0.001, 'max_iter': 100, 'penalty': 'l1', 'solver': 'liblin
ear'}
              precision    recall  f1-score   support

         0.0       0.96      0.99      0.97        76
         1.0       0.91      0.77      0.83        13

    accuracy                           0.96        89
   macro avg       0.94      0.88      0.90        89
weighted avg       0.95      0.96      0.95        89

Macro F1 score of the model on test dataset turns out to be 0.9036796536796536
For model Decision Tree Classifier following are the best parametrs {'max_depth': 15, 'min_samples_leaf': 1}
              precision    recall  f1-score   support

         0.0       0.94      0.99      0.96        76
         1.0       0.89      0.62      0.73        13

    accuracy                           0.93        89
   macro avg       0.91      0.80      0.84        89
weighted avg       0.93      0.93      0.93        89

Macro F1 score of the model on test dataset turns out to be 0.8444055944055944
```


Model = SVC
82.02%
3.37%
3.37%
11.24%
True Label
Predicted Label
0
1
0
1
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1



Model = Logistic Regression
84.27%
1.12%
3.37%
11.24%
True Label
Predicted Label
0
1
0
1
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1



Conclusion:

- From the values obatined from the macro - F1 score, it turns out to be clear that by addressing the class imbalance problem, the performance of best classification model has increased form 90% to 93% (for Logistic Regressor).
- Random Sampler and class_weight sampler gives better performance than sample_weights and SMOTE sampler in regards to macro F1 score