Employee Attrition Prediction

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Importing Libraries

In [209]:

```
pip install scikit-learn imbalanced-learn
```

```
Requirement already satisfied: scikit-learn in c:\users\januk\anaconda3\lib\site-packages (1.3.0)
Requirement already satisfied: imbalanced-learn in c:\users\januk\anaconda3\lib\site-packages (0.11.0)
Requirement already satisfied: numpy>=1.17.3 in c:\users\januk\anaconda3\lib\site-packages (from scikit-learn) (1.20.1)
Requirement already satisfied: scipy>=1.5.0 in c:\users\januk\anaconda3\lib\site-packages (from scikit-learn) (1.6.2)
Requirement already satisfied: joblib>=1.1.1 in c:\users\januk\anaconda3\lib\site-packages (from scikit-learn) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\januk\anaconda3\lib\site-packages (from scikit-learn) (2.1.0)
Note: you may need to restart the kernel to use updated packages.


[notice] A new release of pip is available: 23.1.2 -> 23.2.1
[notice] To update, run: python.exe -m pip install --upgrade pip
```

In [1]:

```python
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import accuracy_score, confusion_matrix
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
import math
```

In [2]:

```python
from sklearn.decomposition import PCA
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
from sklearn.neighbors import KNeighborsClassifier
```

In [3]:

```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

In [4]:

```python
df = pd.read_csv("Employee Attrition.csv")
```

In [5]:
```
df.head()
```

Out[5]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	Emplo
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	

5 rows × 35 columns

In [6]:
```
print(f"Number of records is the dataset : {len(df)}")
print(f"Number of attributes in the dataset : {len(df.columns)}")
```

```
Number of records is the dataset : 1470
Number of attributes in the dataset : 35
```

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
Age                         0
Attrition                   0
BusinessTravel              0
DailyRate                   0
Department                  0
DistanceFromHome            0
Education                   0
EducationField              0
EmployeeCount               0
EmployeeNumber              0
EnvironmentSatisfaction     0
Gender                      0
HourlyRate                  0
JobInvolvement              0
JobLevel                    0
JobRole                     0
JobSatisfaction             0
MaritalStatus               0
MonthlyIncome               0
MonthlyRate                 0
NumCompaniesWorked          0
Over18                      0
OverTime                    0
PercentSalaryHike           0
PerformanceRating           0
RelationshipSatisfaction    0
StandardHours               0
StockOptionLevel            0
TotalWorkingYears           0
TrainingTimesLastYear       0
WorkLifeBalance             0
YearsAtCompany              0
YearsInCurrentRole          0
YearsSinceLastPromotion     0
YearsWithCurrManager        0
dtype: int64
```

In [8]:

```
#To determine ordinal and continuous data attributes
for i in df.columns:
    unique_vals = df[i].unique()
    unique_val_count = len(unique_vals)
    null_vals = df[i].isnull().sum()
    print(f"Attribute {i} has {unique_val_count} unique values and {null_vals} null values.")
```

```
Attribute Age has 43 unique values and 0 null values.
Attribute Attrition has 2 unique values and 0 null values.
Attribute BusinessTravel has 3 unique values and 0 null values.
Attribute DailyRate has 886 unique values and 0 null values.
Attribute Department has 3 unique values and 0 null values.
Attribute DistanceFromHome has 29 unique values and 0 null values.
Attribute Education has 5 unique values and 0 null values.
Attribute EducationField has 6 unique values and 0 null values.
Attribute EmployeeCount has 1 unique values and 0 null values.
Attribute EmployeeNumber has 1470 unique values and 0 null values.
Attribute EnvironmentSatisfaction has 4 unique values and 0 null values.
Attribute Gender has 2 unique values and 0 null values.
Attribute HourlyRate has 71 unique values and 0 null values.
Attribute JobInvolvement has 4 unique values and 0 null values.
Attribute JobLevel has 5 unique values and 0 null values.
Attribute JobRole has 9 unique values and 0 null values.
Attribute JobSatisfaction has 4 unique values and 0 null values.
Attribute MaritalStatus has 3 unique values and 0 null values.
Attribute MonthlyIncome has 1349 unique values and 0 null values.
Attribute MonthlyRate has 1427 unique values and 0 null values.
Attribute NumCompaniesWorked has 10 unique values and 0 null values.
Attribute Over18 has 1 unique values and 0 null values.
Attribute OverTime has 2 unique values and 0 null values.
Attribute PercentSalaryHike has 15 unique values and 0 null values.
Attribute PerformanceRating has 2 unique values and 0 null values.
Attribute RelationshipSatisfaction has 4 unique values and 0 null values.
Attribute StandardHours has 1 unique values and 0 null values.
Attribute StockOptionLevel has 4 unique values and 0 null values.
Attribute TotalWorkingYears has 40 unique values and 0 null values.
Attribute TrainingTimesLastYear has 7 unique values and 0 null values.
Attribute WorkLifeBalance has 4 unique values and 0 null values.
Attribute YearsAtCompany has 37 unique values and 0 null values.
Attribute YearsInCurrentRole has 19 unique values and 0 null values.
Attribute YearsSinceLastPromotion has 16 unique values and 0 null values.
Attribute YearsWithCurrManager has 18 unique values and 0 null values.
```

In [9]:

```
column_list_rank = []
column_list_other = []
for i in df.columns:
    unique_vals = df[i].unique()
    unique_val_count = len(unique_vals)
    if unique_val_count < 10:
        column_list_rank.append(i)
    else:
        column_list_other.append(i)
```

In [10]:
```
column_list_rank
```

Out[10]:
```
['Attrition',
 'BusinessTravel',
 'Department',
 'Education',
 'EducationField',
 'EmployeeCount',
 'EnvironmentSatisfaction',
 'Gender',
 'JobInvolvement',
 'JobLevel',
 'JobRole',
 'JobSatisfaction',
 'MaritalStatus',
 'Over18',
 'OverTime',
 'PerformanceRating',
 'RelationshipSatisfaction',
 'StandardHours',
 'StockOptionLevel',
 'TrainingTimesLastYear',
 'WorkLifeBalance']
```

In [11]:
```
df["StandardHours"].unique()
```

Out[11]:
```
array([80], dtype=int64)
```

In [12]:
```
df["Over18"].unique()
```

Out[12]:
```
array(['Y'], dtype=object)
```

In [13]:
```
df["EmployeeCount"].unique()
```

Out[13]:
```
array([1], dtype=int64)
```

- We can remove the StandardHours, EmployeeCount, Over18 and EmployeeNumber attributes since there is no any effect from those attribute for the training of our model.
- We also reomove Attrition since it's our target feature.

In [14]:
```
column_list_rank.remove("StandardHours")
column_list_rank.remove("EmployeeCount")
column_list_rank.remove("Attrition")
column_list_rank.remove("Over18")
```

In [15]:
```
column_list_other.remove("EmployeeNumber")
```

In [16]:
```
target = "Attrition"
```

Data Preprocessing

In [17]:

```
for i in column_list_rank:
    print(f"Feature Name : {i}")
    print(df[i].value_counts())
    print("\n")
```

```
Feature Name : BusinessTravel
Travel_Rarely        1043
Travel_Frequently     277
Non-Travel            150
Name: BusinessTravel, dtype: int64


Feature Name : Department
Research & Development    961
Sales                     446
Human Resources            63
Name: Department, dtype: int64


Feature Name : Education
3    572
4    398
2    282
1    170
```

- We have to encode BusinessTravel, Department, EducationField, Gender, JobRole, MaritalStatus and OverTime

In [18]:

```
df1 = df.copy(deep=True)
```

In [19]:

```
le = LabelEncoder()

for i in column_list_rank:
    if df1[i].dtype != 'int64':
        df1[i]= le.fit_transform(df1[i])
```

In [20]:

```
df1["Attrition"] = le.fit_transform(df1["Attrition"])
```

In [21]:

```
df1.head()
```

Out[21]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	Employe
0	41	1	2	1102	2	1	2	1	1	
1	49	0	1	279	1	8	1	1	1	
2	37	1	2	1373	1	2	2	4	1	
3	33	0	1	1392	1	3	4	1	1	
4	27	0	2	591	1	2	1	3	1	

5 rows × 35 columns

In [22]:

```
df1 = pd.concat([df1[column_list_rank], df1[column_list_other], df1[target]], axis=1)
```

In [23]:
```
df1
```

Out[23]:

	BusinessTravel	Department	Education	EducationField	EnvironmentSatisfaction	Gender	JobInvolvement	JobLevel	JobRole
0	2	2	2	1	2	0	3	2	7
1	1	1	1	1	3	1	2	2	6
2	2	1	2	4	4	1	2	1	2
3	1	1	4	1	4	0	3	1	6
4	2	1	1	3	1	1	3	1	2
...	...	...	...	...	...	...	...	...	..
1465	1	1	2	3	3	1	4	2	2
1466	2	1	1	3	4	1	2	3	0
1467	2	1	3	1	2	1	4	2	4
1468	1	2	3	3	4	1	2	2	7
1469	2	1	3	3	2	1	4	2	2

1470 rows × 31 columns

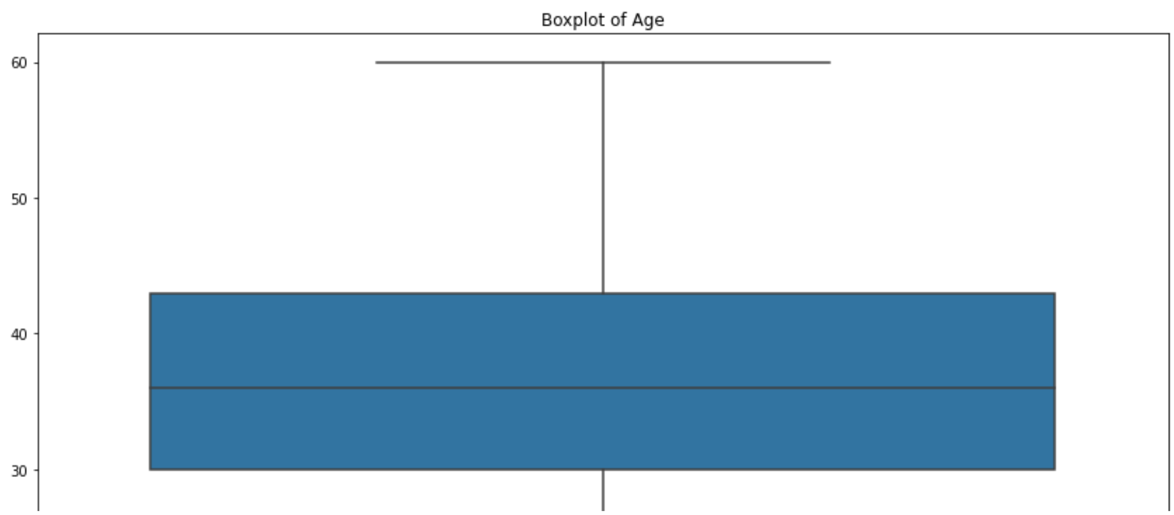
Outlier Detection and Removal

In [24]:
```
df1[column_list_other].describe()
```

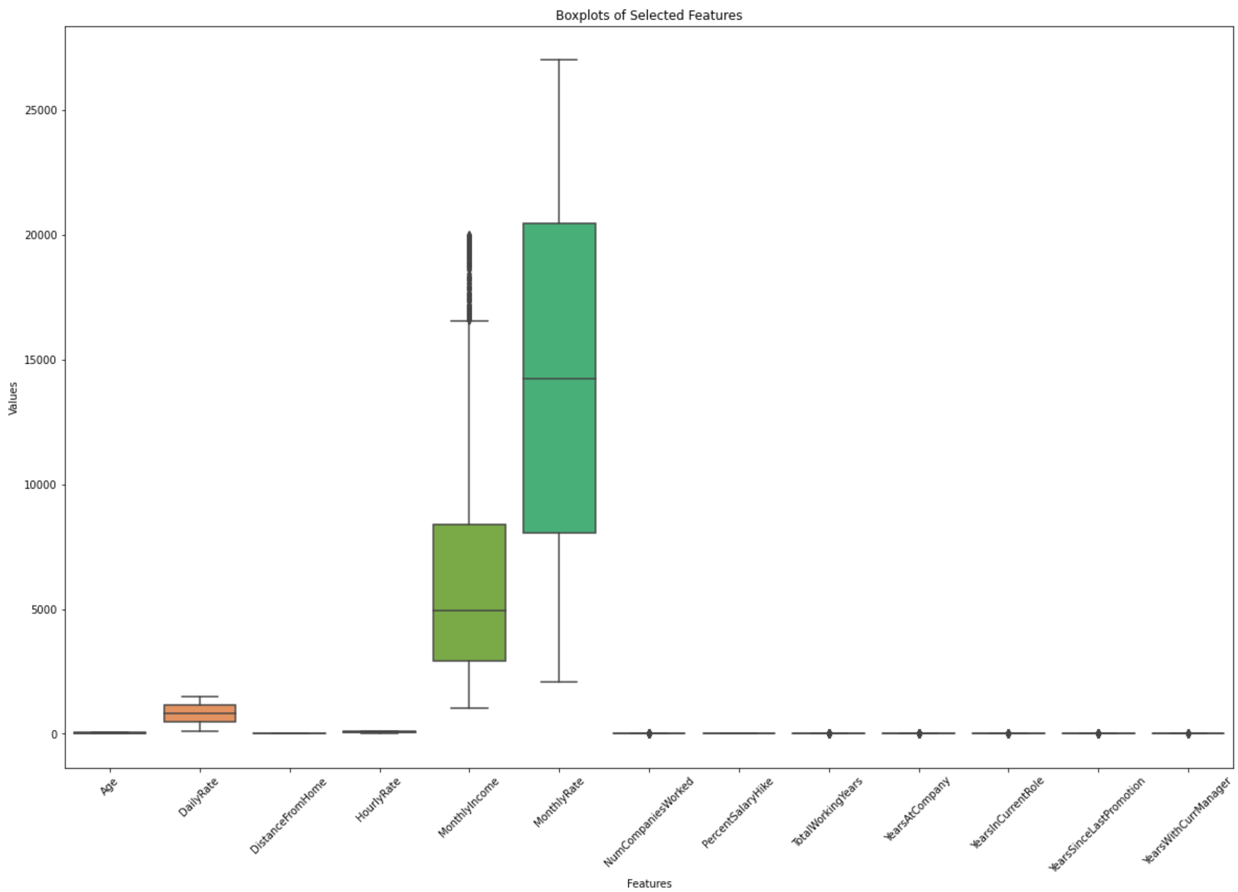
Out[24]:

	Age	DailyRate	DistanceFromHome	HourlyRate	MonthlyIncome	MonthlyRate	NumCompaniesWorked	PercentS
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000	147
mean	36.923810	802.485714	9.192517	65.891156	6502.931293	14313.103401	2.693197	1
std	9.135373	403.509100	8.106864	20.329428	4707.956783	7117.786044	2.498009	
min	18.000000	102.000000	1.000000	30.000000	1009.000000	2094.000000	0.000000	1
25%	30.000000	465.000000	2.000000	48.000000	2911.000000	8047.000000	1.000000	1
50%	36.000000	802.000000	7.000000	66.000000	4919.000000	14235.500000	2.000000	1
75%	43.000000	1157.000000	14.000000	83.750000	8379.000000	20461.500000	4.000000	1
max	60.000000	1499.000000	29.000000	100.000000	19999.000000	26999.000000	9.000000	2

In [25]:
```
fig, axes = plt.subplots(len(column_list_other), 1, figsize=(12, 7 * len(column_list_other)), sharex=Fals

# Step 1: Show Boxplots for each selected feature
for i, feature in enumerate(column_list_other):
    sb.boxplot(data=df[feature], ax=axes[i])
    axes[i].set_title(f'Boxplot of {feature}')
    axes[i].set_xlabel('Value')

plt.tight_layout()
plt.show()
```



In [26]:
```
subset_df = df[column_list_other]

# Plot boxplots for each selected feature
plt.figure(figsize=(20, 13))
sb.boxplot(data=subset_df)
plt.title('Boxplots of Selected Features')
plt.xlabel('Features')
plt.ylabel('Values')
plt.xticks(rotation=45)
plt.show()
```



In [27]:
```
(df["MonthlyIncome"].values > 15000).sum()
```

Out[27]: 133

- Better to use flooring instead of removing samples since we may loose many number of rows from the dataset

In [28]:

```
def floor_outliers_iqr(df1, feature):
    Q1 = df1[feature].quantile(0.25)
    Q3 = df1[feature].quantile(0.75)
    IQR = Q3 - Q1

    # Define the lower and upper bounds to handle outliers
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Apply flooring (lower bound) and ceiling (upper bound) for outliers
    df1[feature] = df1[feature].apply(lambda x: lower_bound if x < lower_bound else (upper_bound if x > u
    return df1

# Handle outliers for each selected feature
for feature in column_list_other:
    df1 = floor_outliers_iqr(df1, feature)

# Display the DataFrame after handling outliers by flooring
print("DataFrame after handling outliers by flooring:")

df1
```

```
DataFrame after handling outliers by flooring:
```

Out[28]:

	BusinessTravel	Department	Education	EducationField	EnvironmentSatisfaction	Gender	JobInvolvement	JobLevel	JobRole
0	2	2	2	1	2	0	3	2	7
1	1	1	1	1	3	1	2	2	6
2	2	1	2	4	4	1	2	1	2
3	1	1	4	1	4	0	3	1	6
4	2	1	1	3	1	1	3	1	2
...	...	...	...	...	...	...	...	...	..
1465	1	1	2	3	3	1	4	2	2
1466	2	1	1	3	4	1	2	3	0
1467	2	1	3	1	2	1	4	2	4
1468	1	2	3	3	4	1	2	2	7
1469	2	1	3	3	2	1	4	2	2

1470 rows × 31 columns

In [29]:

```
df1[column_list_other].describe()
```

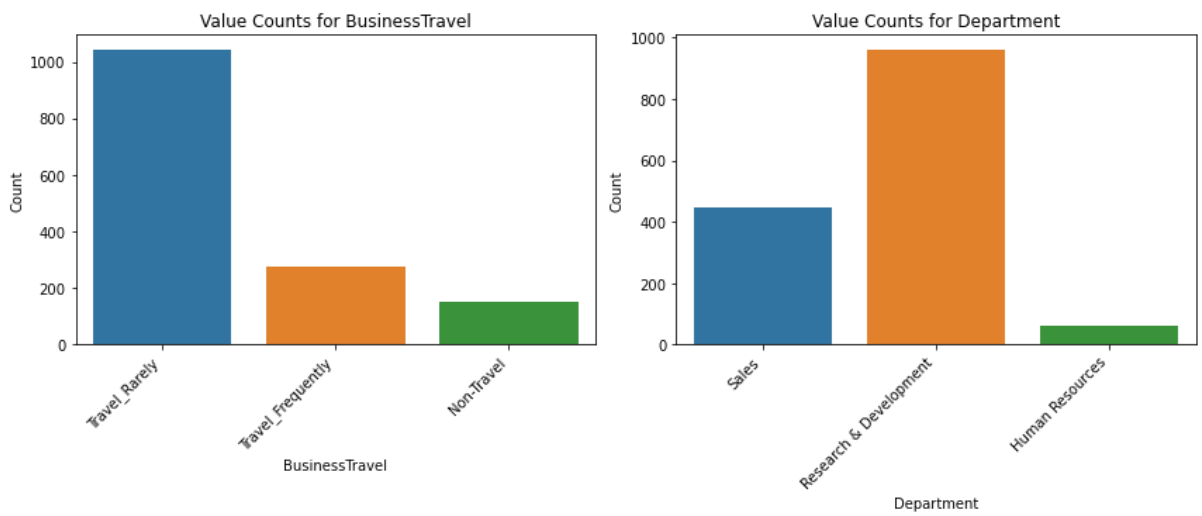
Out[29]:

	Age	DailyRate	DistanceFromHome	HourlyRate	MonthlyIncome	MonthlyRate	NumCompaniesWorked	PercentS
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000	147
mean	36.923810	802.485714	9.192517	65.891156	6361.891837	14313.103401	2.675510	1
std	9.135373	403.509100	8.106864	20.329428	4353.345470	7117.786044	2.454656	
min	18.000000	102.000000	1.000000	30.000000	1009.000000	2094.000000	0.000000	1
25%	30.000000	465.000000	2.000000	48.000000	2911.000000	8047.000000	1.000000	1
50%	36.000000	802.000000	7.000000	66.000000	4919.000000	14235.500000	2.000000	1
75%	43.000000	1157.000000	14.000000	83.750000	8379.000000	20461.500000	4.000000	1
max	60.000000	1499.000000	29.000000	100.000000	16581.000000	26999.000000	8.500000	2

Feature Visualizations

- Let us visualize ordinal and nominal features with value counts

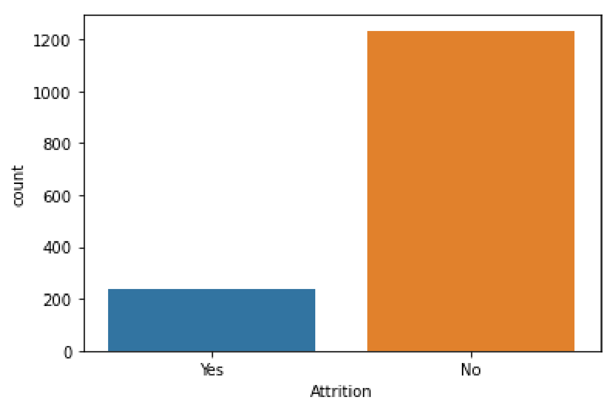
In [30]:
```
num_rows = len(column_list_rank) // 2 + len(column_list_rank) % 2
fig, axes = plt.subplots(num_rows, 2, figsize=(12, 5 * num_rows))

# Flatten the axes array for easy iteration
axes = axes.flatten()

# Plot value counts for each selected feature using Seaborn
for i, feature in enumerate(column_list_rank):
    ax = axes[i]
    sb.countplot(data=df, x=feature, ax=ax)
    ax.set_title(f'Value Counts for {feature}')
    ax.set_xlabel(feature)
    ax.set_ylabel('Count')
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')

# Hide any remaining empty subplots
for i in range(len(column_list_rank), len(axes)):
    axes[i].axis('off')

plt.tight_layout()
plt.show()
```



- Let us visualize target feature with value counts

In [31]:
```
sb.countplot(data=df, x="Attrition")
```

Out[31]: <AxesSubplot:xlabel='Attrition', ylabel='count'>



- We can see that the two classes are imbalanced.

In [32]:
```
X = pd.concat([df1[column_list_rank], df1[column_list_other]], axis=1)
```

In [33]:
```
y = df1[target]
```

In [34]:
```
X
```

Out[34]:

	BusinessTravel	Department	Education	EducationField	EnvironmentSatisfaction	Gender	JobInvolvement	JobLevel	JobRole
0	2	2	2	1	2	0	3	2	7
1	1	1	1	1	3	1	2	2	6
2	2	1	2	4	4	1	2	1	2
3	1	1	4	1	4	0	3	1	6
4	2	1	1	3	1	1	3	1	2
...	...	...	...	...	...	...	...	...	..
1465	1	1	2	3	3	1	4	2	2
1466	2	1	1	3	4	1	2	3	0
1467	2	1	3	1	2	1	4	2	4
1468	1	2	3	3	4	1	2	2	7
1469	2	1	3	3	2	1	4	2	2

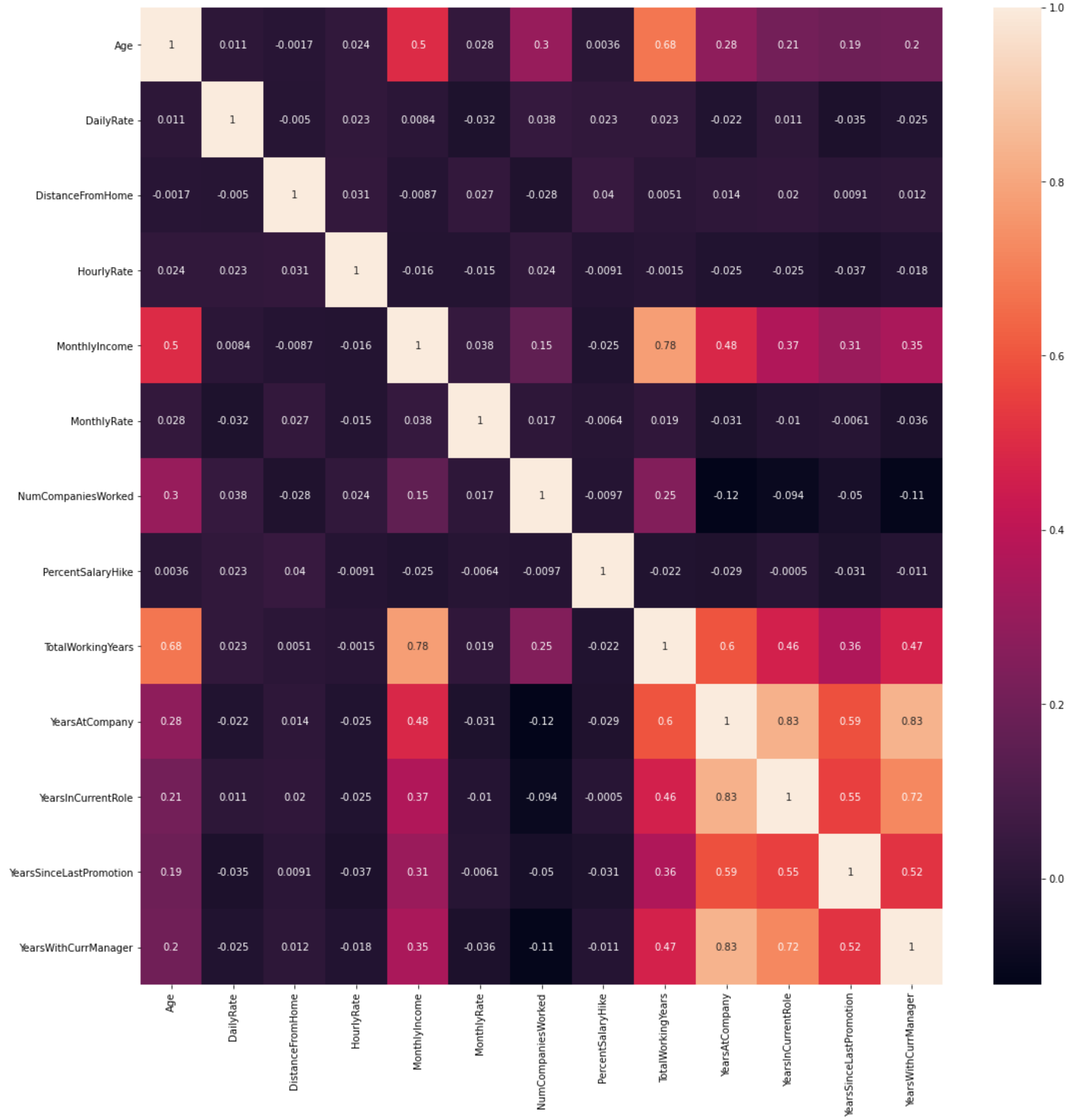
1470 rows × 30 columns

In [35]:
```
y
```

Out[35]:
```
0       1
1       0
2       1
3       0
4       0
       ..
1465    0
1466    0
1467    0
1468    0
1469    0
Name: Attrition, Length: 1470, dtype: int32
```

In [36]:
```
corr = df1[column_list_other].corr()
```

In [37]:
```
plt.figure(figsize = (18, 18))
sb.heatmap(corr, annot=True)
plt.show()
```



Data Resampling to Solve Imbalanced Class Problem

- We will use Random Oversampling and Eandom Undesampling to overcome imbalanced class problem

1. Random Oversampling

In [38]:
```
#Normalizing the features
scaler = MinMaxScaler()
scaler.fit(X)
X = scaler.transform(X)
```

In [39]:
```
X[0]
```

Out[39]:
```
array([1.        , 1.        , 0.25      , 0.2       , 0.33333333,
       0.        , 0.66666667, 0.25      , 0.875     , 1.        ,
       1.        , 1.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.54761905, 0.71581961, 0.        ,
       0.91428571, 0.32006165, 0.6980526 , 0.94117647, 0.        ,
       0.28070175, 0.33333333, 0.27586207, 0.        , 0.34482759])
```

In [40]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=42)
#Train test split
#X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=0)
```

In [41]:
```
ro = RandomOverSampler(random_state=0)
X_train_ro, y_train_ro = ro.fit_resample(X_train, y_train)
```

In [42]:
```
y = 0
n = 0

for i in y_train_ro.values:
    if i == 1:
        y = y + 1
    else:
        n = n + 1

print(f"Number of No's is {n} and number of Yes's is {y}")
```

```
Number of No's is 986 and number of Yes's is 986
```

2. Random Undersampling

In [43]:
```
ru = RandomUnderSampler(random_state=0)
X_train_ru, y_train_ru = ru.fit_resample(X_train, y_train)
```

In [44]:
```
y = 0
n = 0

for i in y_train_ru.values:
    if i == 1:
        y = y + 1
    else:
        n = n + 1

print(f"Number of No's is {n} and number of Yes's is {y}")
```

```
Number of No's is 190 and number of Yes's is 190
```

Feature Extraction

In [45]:
```
n_components = 2
pca = PCA(n_components=n_components)
X_train_pca = pca.fit_transform(X_train)
X_test_pca = pca.fit_transform(X_test)
```

In [46]:
```
clf = SVC(kernel='linear', probability=True)
clf.fit(X_train_pca, y_train)
```

Out[46]:
```
SVC
SVC(kernel='linear', probability=True)
```

In [47]:
```
y_pred_pca = clf.predict(X_test_pca)
```

In [48]:
```
accuracy1 = accuracy_score(y_test, y_pred_pca)
print(f"Accuracy of original dataset : {accuracy1}")
```

```
Accuracy of original dataset : 0.8401360544217688
```

- We can consider extracted features for classifications as well as without feature extraction

Classification

In [49]:
```
#Function to plot confusion matrix
def conf_matrix(labels, algo):
    datasets = ["Original Data", "Oversampled Data", "Undersampled Data", "Feature Extracted Data"]
    for i in range(4):
        cm = confusion_matrix(labels[i][0], labels[i][1])
        sb.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=['Predicted 0', 'Predicted 1'],
                yticklabels=['Actual 0', 'Actual 1'])
        plt.xlabel('Predicted')
        plt.ylabel('Actual')
        plt.title(f"{algo} - {datasets[i]}")
        plt.show()
```

In [50]:
```
#Function to plot accuracies
def accu_plot(accuracies, algo):
    datasets = ["Original Data", "Oversampled Data", "Undersampled Data", "Feature Extracted Data"]
    plt.figure(figsize=(10, 6))
    plt.bar(datasets, accuracies, color='skyblue')

    plt.xlabel('Datasets')
    plt.ylabel(f"Accuracy for {algo}")
    plt.title(f"{algo} Accuracies")

    for i in range(len(datasets)):
        plt.text(i, accuracies[i] + 0.01, f'{accuracies[i]:.2f}', ha='center')

    plt.ylim(0, 1.0)
    plt.show()
```

1. Support Vector Machine

In [51]:
```
# Train SVC on original data
clf = SVC(kernel='linear', probability=True)
clf.fit(X_train, y_train)

# Train SVC on randomly oversampled data
clf_ro = SVC(kernel='linear', probability=True)
clf_ro.fit(X_train_ro, y_train_ro)

# Train SVC on randomly undersampled data
clf_ru = SVC(kernel='linear', probability=True)
clf_ru.fit(X_train_ru, y_train_ru)

# Train SVC on feature extracted original data
clf_pca = SVC(kernel='linear', probability=True)
clf_pca.fit(X_train_pca, y_train)
```

Out[51]:
```
SVC
SVC(kernel='linear', probability=True)
```

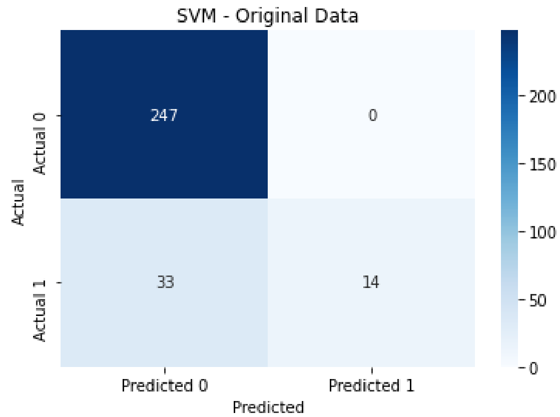
In [52]:
```
y_pred = clf.predict(X_test)
y_pred_ro = clf_ro.predict(X_test)
y_pred_ru = clf_ru.predict(X_test)
y_pred_pca = clf_pca.predict(X_test_pca)
```

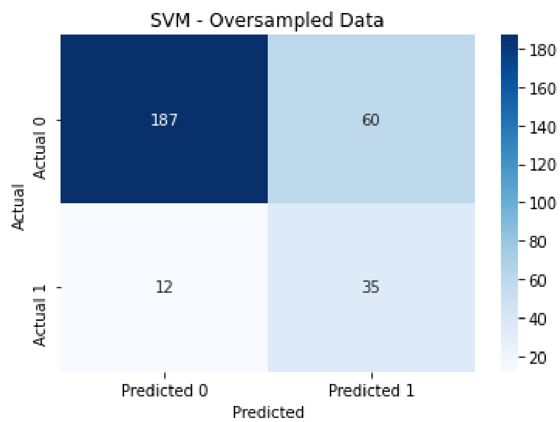
In [53]:
```
accuracy1_svm = accuracy_score(y_test, y_pred)
accuracy2_svm = accuracy_score(y_test, y_pred_ro)
accuracy3_svm = accuracy_score(y_test, y_pred_ru)
accuracy4_svm = accuracy_score(y_test, y_pred_pca)
```

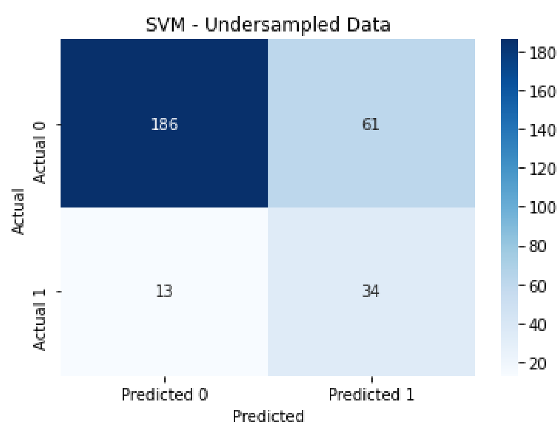
In [54]:
```
print(f"Accuracy of original dataset : {accuracy1_svm}")
print(f"Accuracy of oversampled dataset : {accuracy2_svm}")
print(f"Accuracy of undersampled dataset : {accuracy3_svm}")
print(f"Accuracy of feature extracted dataset : {accuracy4_svm}")
```

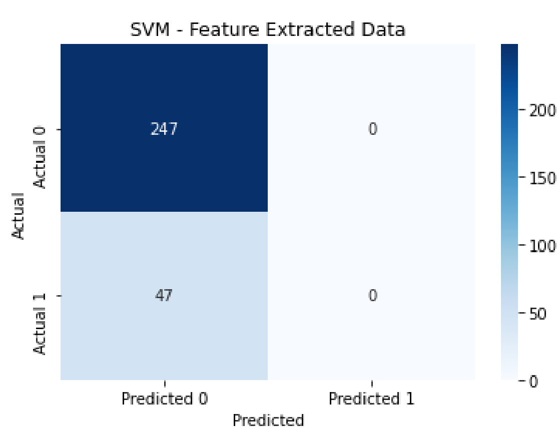
```
Accuracy of original dataset : 0.8877551020408163
Accuracy of oversampled dataset : 0.7551020408163265
Accuracy of undersampled dataset : 0.7482993197278912
Accuracy of feature extracted dataset : 0.8401360544217688
```

In [55]:
```
conf_matrix([(y_test, y_pred),(y_test, y_pred_ro),(y_test, y_pred_ru),(y_test, y_pred_pca)], "SVM")
```



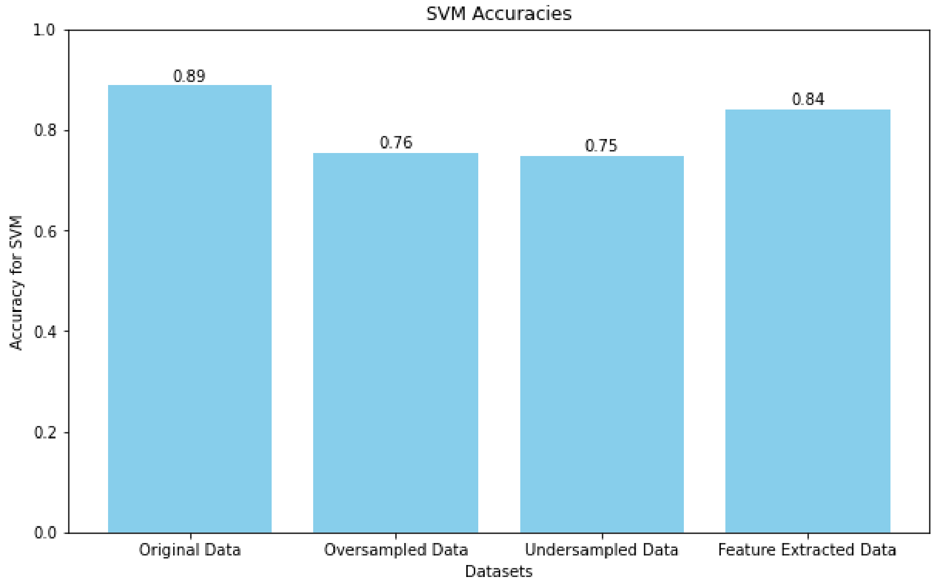






- It is to be noted that even though orifginal dataset gives high accuracies, it most correctly detects 0 class only. So in this case

In [56]:
```
accu_plot([accuracy1_svm, accuracy2_svm, accuracy3_svm, accuracy4_svm], "SVM")
```



2. Logistics Regression

In [57]:
```
lr = LogisticRegression()
lr_ro = LogisticRegression()
lr_ru = LogisticRegression()
lr_pca = LogisticRegression()
```

In [58]:
```
lr.fit(X_train, y_train)
lr_ro.fit(X_train_ro, y_train_ro)
lr_ru.fit(X_train_ru, y_train_ru)
lr_pca.fit(X_train_pca, y_train)
```

Out[58]:
```
▾ LogisticRegression
LogisticRegression()
```

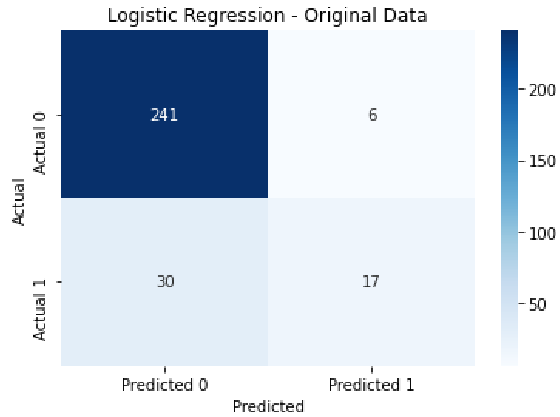
In [59]:
```
y_pred = lr.predict(X_test)
y_pred_ro = lr_ro.predict(X_test)
y_pred_ru = lr_ru.predict(X_test)
y_pred_pca = lr_pca.predict(X_test_pca)
```

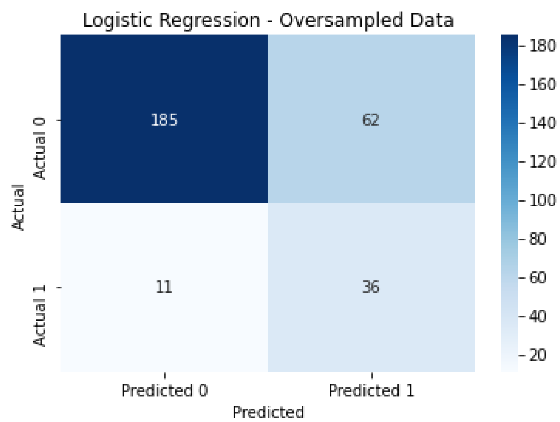
In [60]:
```
accuracy1_lr = accuracy_score(y_test, y_pred)
accuracy2_lr = accuracy_score(y_test, y_pred_ro)
accuracy3_lr = accuracy_score(y_test, y_pred_ru)
accuracy4_lr = accuracy_score(y_test, y_pred_pca)
```

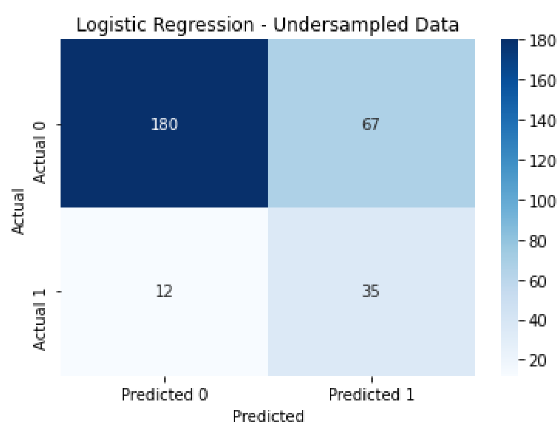
In [61]:
```
print(f"Accuracy of original dataset : {accuracy1_lr}")
print(f"Accuracy of oversampled dataset : {accuracy2_lr}")
print(f"Accuracy of undersampled dataset : {accuracy3_lr}")
print(f"Accuracy of feature extracted dataset : {accuracy4_lr}")
```

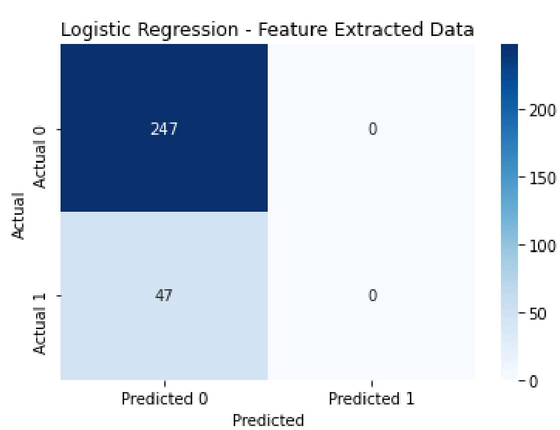
```
Accuracy of original dataset : 0.8775510204081632
Accuracy of oversampled dataset : 0.7517006802721088
Accuracy of undersampled dataset : 0.7312925170068028
Accuracy of feature extracted dataset : 0.8401360544217688
```

In [62]:
```
conf_matrix([(y_test, y_pred),(y_test, y_pred_ro),(y_test, y_pred_ru),(y_test, y_pred_pca)], "Logistic Re
```

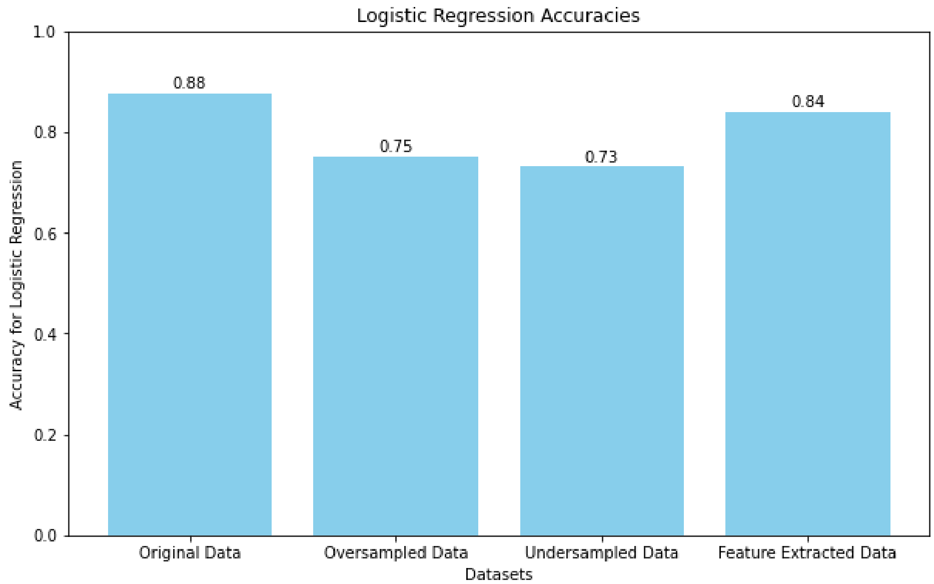








In [63]:
```
accu_plot([accuracy1_lr, accuracy2_lr, accuracy3_lr, accuracy4_lr], "Logistic Regression")
```



3. Decision Tree

In [64]:
```
dt = DecisionTreeClassifier()
dt_ro = DecisionTreeClassifier()
dt_ru = DecisionTreeClassifier()
dt_pca = DecisionTreeClassifier()
```

In [65]:
```
dt.fit(X_train, y_train)
dt_ro.fit(X_train_ro, y_train_ro)
dt_ru.fit(X_train_ru, y_train_ru)
dt_pca.fit(X_train_pca, y_train)
```

Out[65]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

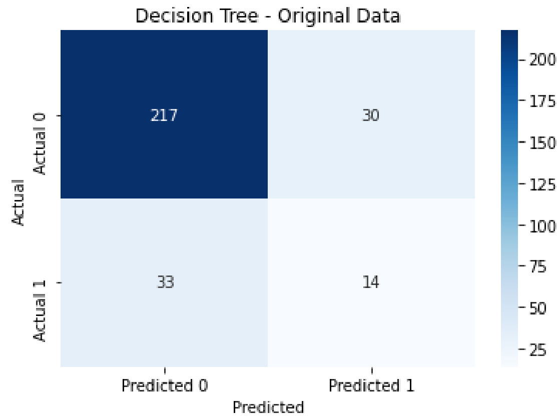
In [66]:
```
y_pred = dt.predict(X_test)
y_pred_ro = dt_ro.predict(X_test)
y_pred_ru = dt_ru.predict(X_test)
y_pred_pca = dt_pca.predict(X_test_pca)
```

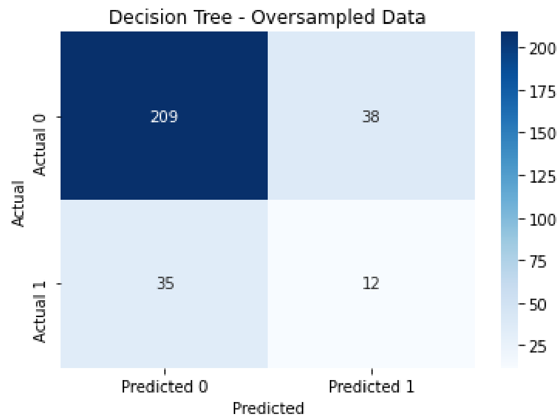
In [67]:
```
accuracy1_dt = accuracy_score(y_test, y_pred)
accuracy2_dt = accuracy_score(y_test, y_pred_ro)
accuracy3_dt = accuracy_score(y_test, y_pred_ru)
accuracy4_dt = accuracy_score(y_test, y_pred_pca)
```

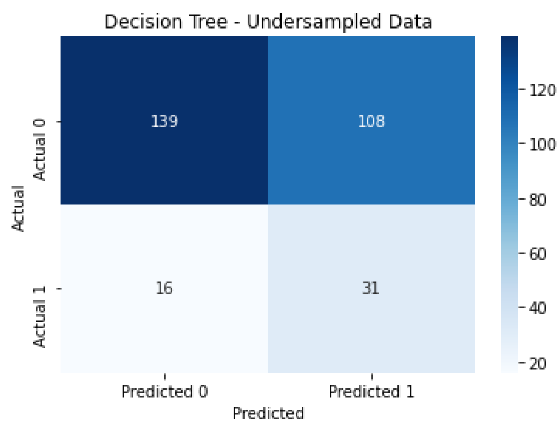
In [68]:
```
print(f"Accuracy of original dataset : {accuracy1_dt}")
print(f"Accuracy of oversampled dataset : {accuracy2_dt}")
print(f"Accuracy of undersampled dataset : {accuracy3_dt}")
print(f"Accuracy of feature extracted dataset : {accuracy4_dt}")
```

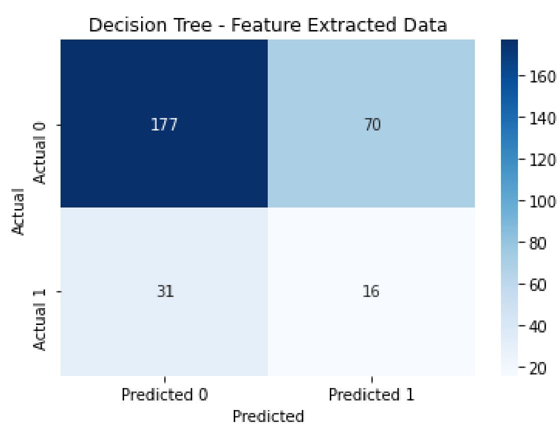
```
Accuracy of original dataset : 0.7857142857142857
Accuracy of oversampled dataset : 0.7517006802721088
Accuracy of undersampled dataset : 0.5782312925170068
Accuracy of feature extracted dataset : 0.6564625850340136
```

In [69]:
```
conf_matrix([(y_test, y_pred),(y_test, y_pred_ro),(y_test, y_pred_ru),(y_test, y_pred_pca)], "Decision Tr
```

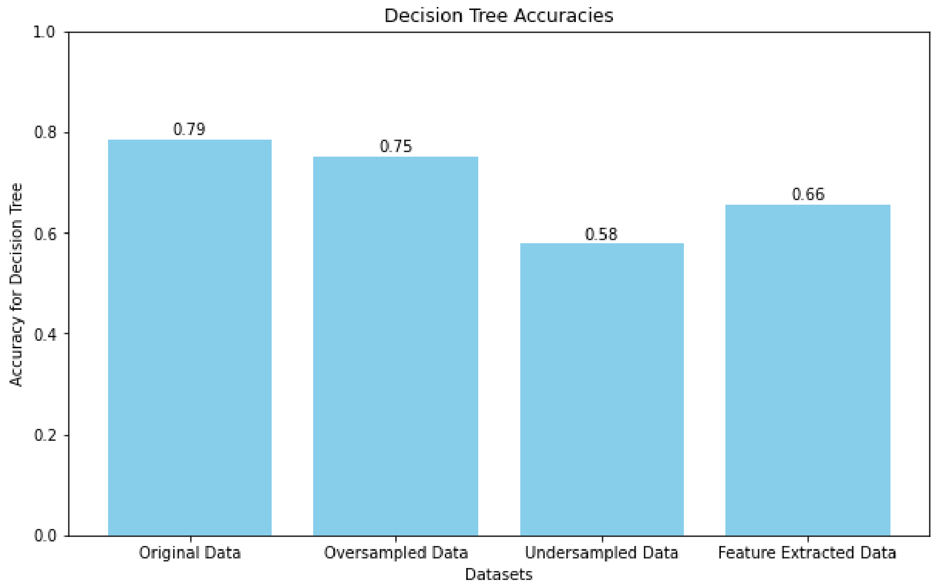








In [70]:
```python
accu_plot([accuracy1_dt, accuracy2_dt, accuracy3_dt, accuracy4_dt], "Decision Tree")
```



4. Random Forest

In [71]:
```python
rf = RandomForestClassifier()
rf_ro = RandomForestClassifier()
rf_ru = RandomForestClassifier()
rf_pca = RandomForestClassifier()
```

In [72]:
```python
rf.fit(X_train, y_train)
rf_ro.fit(X_train_ro, y_train_ro)
rf_ru.fit(X_train_ru, y_train_ru)
rf_pca.fit(X_train_pca, y_train)
```

Out[72]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

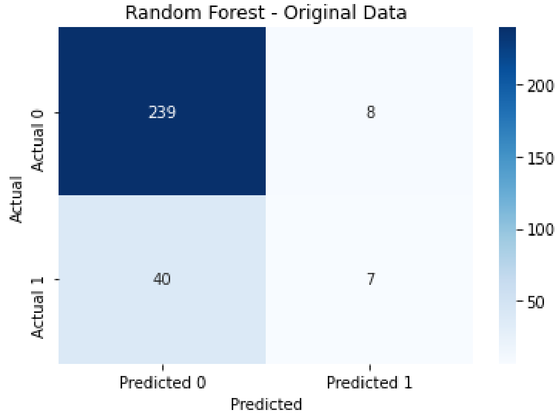
In [73]:
```python
y_pred = rf.predict(X_test)
y_pred_ro = rf_ro.predict(X_test)
y_pred_ru = rf_ru.predict(X_test)
y_pred_pca = rf_pca.predict(X_test_pca)
```

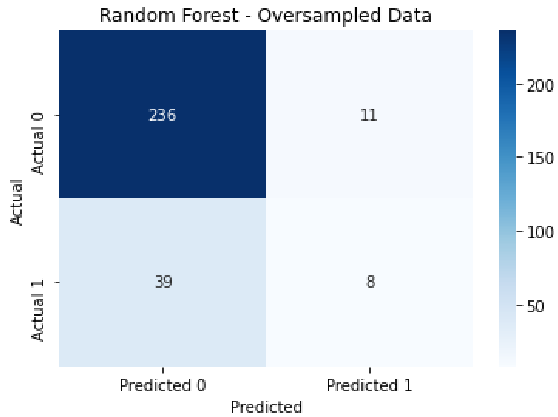
In [74]:
```python
accuracy1_rf = accuracy_score(y_test, y_pred)
accuracy2_rf = accuracy_score(y_test, y_pred_ro)
accuracy3_rf = accuracy_score(y_test, y_pred_ru)
accuracy4_rf = accuracy_score(y_test, y_pred_pca)
```

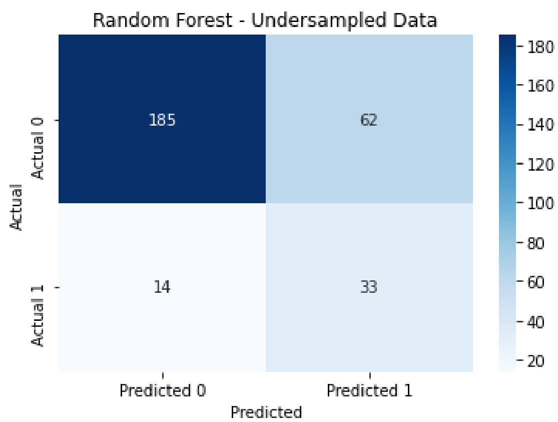
In [75]:
```python
print(f"Accuracy of original dataset : {accuracy1_rf}")
print(f"Accuracy of oversampled dataset : {accuracy2_rf}")
print(f"Accuracy of undersampled dataset : {accuracy3_rf}")
print(f"Accuracy of feature extracted dataset : {accuracy4_rf}")
```

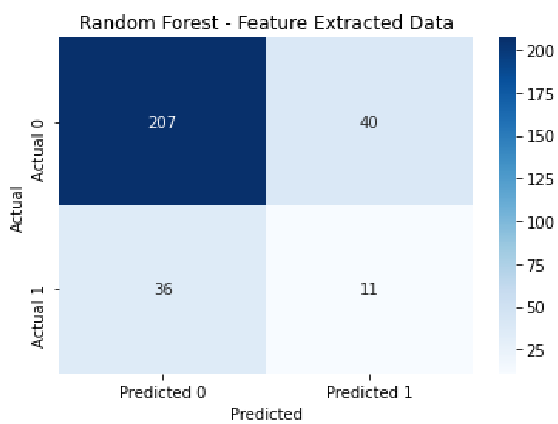
```
Accuracy of original dataset : 0.8367346938775511
Accuracy of oversampled dataset : 0.8299319727891157
Accuracy of undersampled dataset : 0.7414965986394558
Accuracy of feature extracted dataset : 0.7414965986394558
```

In [76]:
```
conf_matrix([(y_test, y_pred),(y_test, y_pred_ro),(y_test, y_pred_ru),(y_test, y_pred_pca)], "Random Fore
```

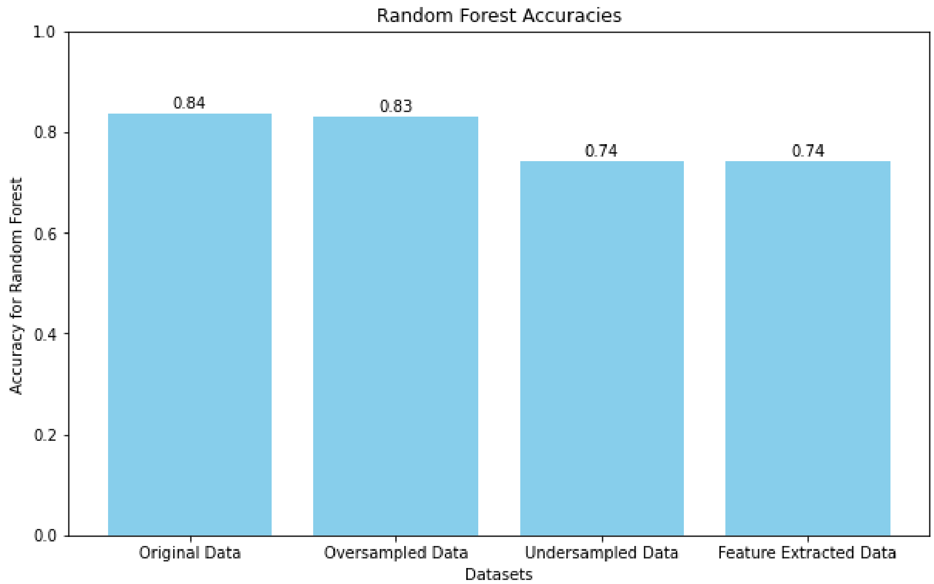








In [77]:
```
accu_plot([accuracy1_rf, accuracy2_rf, accuracy3_rf, accuracy4_rf], "Random Forest")
```



5. XG-Boost

In [78]:
```
xg = xgb.XGBClassifier()
xg_ro = xgb.XGBClassifier()
xg_ru = xgb.XGBClassifier()
xg_pca = xgb.XGBClassifier()
```

In [79]:
```
xg.fit(X_train, y_train)
xg_ro.fit(X_train_ro, y_train_ro)
xg_ru.fit(X_train_ru, y_train_ru)
xg_pca.fit(X_train_pca, y_train)
```

Out[79]:

XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
```

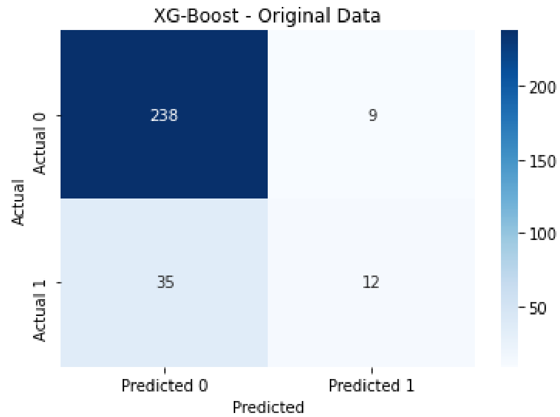
In [80]:
```
y_pred = xg.predict(X_test)
y_pred_ro = xg_ro.predict(X_test)
y_pred_ru = xg_ru.predict(X_test)
y_pred_pca = xg_pca.predict(X_test_pca)
```

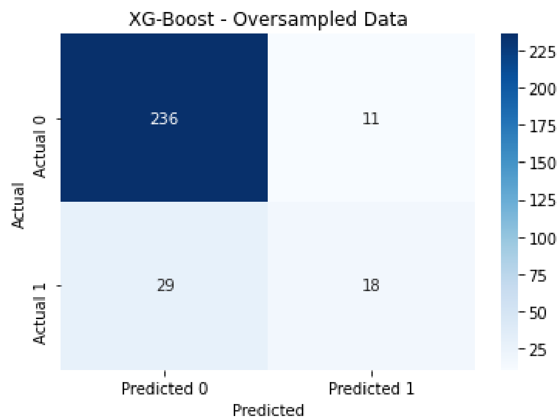
In [81]:
```
accuracy1_xg = accuracy_score(y_test, y_pred)
accuracy2_xg = accuracy_score(y_test, y_pred_ro)
accuracy3_xg = accuracy_score(y_test, y_pred_ru)
accuracy4_xg = accuracy_score(y_test, y_pred_pca)
```

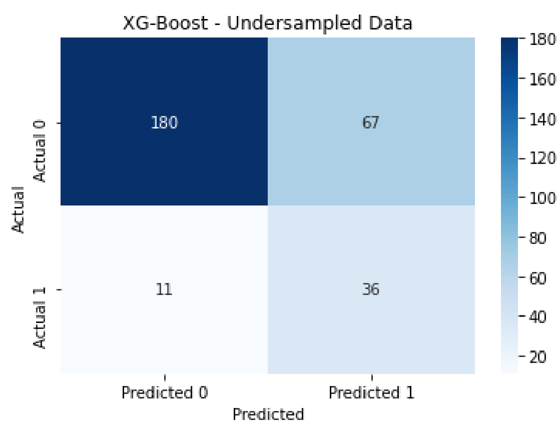
In [82]:
```
print(f"Accuracy of original dataset : {accuracy1_xg}")
print(f"Accuracy of oversampled dataset : {accuracy2_xg}")
print(f"Accuracy of undersampled dataset : {accuracy3_xg}")
print(f"Accuracy of feature extracted dataset : {accuracy4_xg}")
```

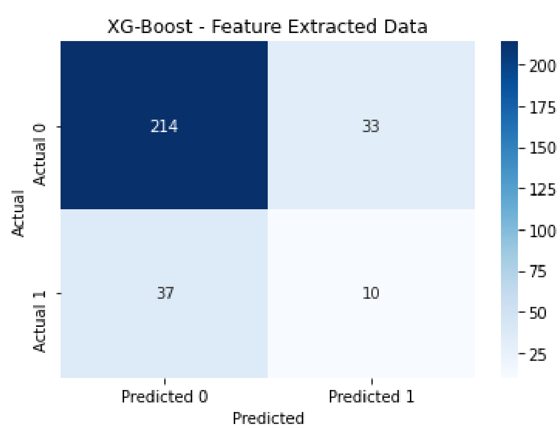
```
Accuracy of original dataset : 0.8503401360544217
Accuracy of oversampled dataset : 0.8639455782312925
Accuracy of undersampled dataset : 0.7346938775510204
Accuracy of feature extracted dataset : 0.7619047619047619
```

In [83]:
```
conf_matrix([(y_test, y_pred),(y_test, y_pred_ro),(y_test, y_pred_ru),(y_test, y_pred_pca)], "XG-Boost")
```

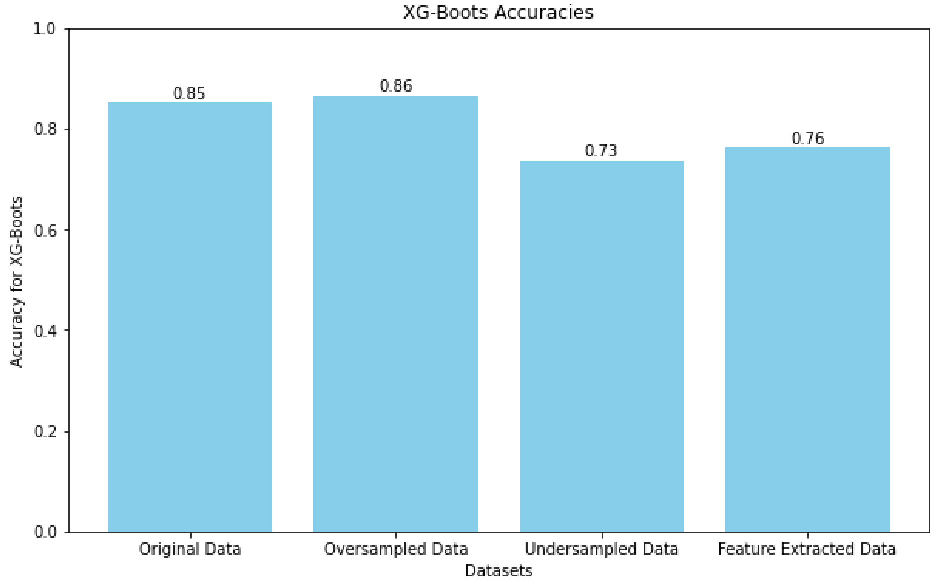








In [84]:
```
accu_plot([accuracy1_xg, accuracy2_xg, accuracy3_xg, accuracy4_xg], "XG-Boots")
```



6. KNN - Classifier

- We will check our accuracies with k values in the range 1 - 10

In [86]:

```
k_values = list(range(1, 11))

accuracy_scores = {}
k_val = []
acc_val = []
max_accuracy = 0
labels = []
accus = []

for k in k_values:
    accu = []
    knn = KNeighborsClassifier(n_neighbors=k)
    knn_ro = KNeighborsClassifier(n_neighbors=k)
    knn_ru = KNeighborsClassifier(n_neighbors=k)
    knn_pca = KNeighborsClassifier(n_neighbors=k)

    knn.fit(X_train, y_train)
    knn_ro.fit(X_train_ro, y_train_ro)
    knn_ru.fit(X_train_ru, y_train_ru)
    knn_pca.fit(X_train_pca, y_train)

    y_pred = knn.predict(X_test)
    y_pred_ro = knn_ro.predict(X_test)
    y_pred_ru = knn_ru.predict(X_test)
    y_pred_pca = knn_pca.predict(X_test_pca)

    knn1 = accuracy_score(y_test, y_pred)
    knn2 = accuracy_score(y_test, y_pred_ro)
    knn3 = accuracy_score(y_test, y_pred_ru)
    knn4 = accuracy_score(y_test, y_pred_pca)

    if knn1 > max_accuracy:
        labels.clear()
        labels.append((y_test, y_pred))
        labels.append((y_test, y_pred_ro))
        labels.append((y_test, y_pred_ru))
        labels.append((y_test, y_pred_pca))

        accus.clear()
        accus.append(knn1)
        accus.append(knn2)
        accus.append(knn3)
        accus.append(knn4)

    accu.append(knn1)
    accu.append(knn2)
    accu.append(knn3)
    accu.append(knn4)

    k_val.append(k)
    acc_val.append(knn1)

    accuracy_scores[k] = accu
```

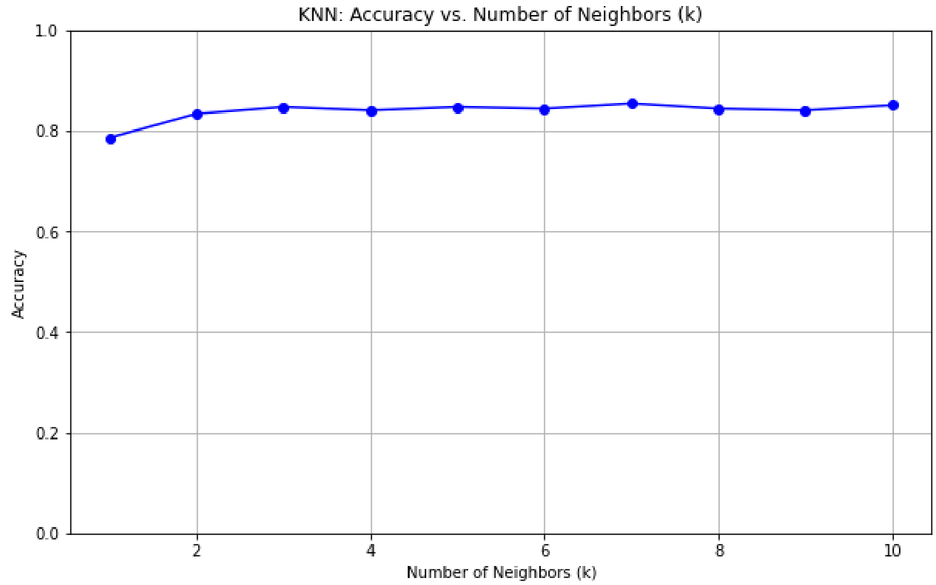
In [87]:
```
#Displaying all accuraries values for 4 datasets for each k
accuracy_scores
```

Out[87]:
```
{1: [0.7857142857142857,
  0.7857142857142857,
  0.6768707482993197,
  0.6938775510204082],
 2: [0.8333333333333334,
  0.7857142857142857,
  0.7925170068027211,
  0.8095238095238095],
 3: [0.8469387755102041,
  0.7857142857142857,
  0.7312925170068028,
  0.7959183673469388],
 4: [0.8401360544217688,
  0.7891156462585034,
  0.7687074829931972,
  0.826530612244898],
 5: [0.8469387755102041,
  0.7448979591836735,
  0.7108843537414966,
  0.8197278911564626],
 6: [0.8435374149659864,
  0.7619047619047619,
  0.7687074829931972,
  0.8367346938775511],
 7: [0.8537414965986394,
  0.7414965986394558,
  0.7108843537414966,
  0.8367346938775511],
 8: [0.8435374149659864,
  0.7653061224489796,
  0.7585034013605442,
  0.8333333333333334],
 9: [0.8401360544217688,
  0.7448979591836735,
  0.7210884353741497,
  0.8367346938775511],
 10: [0.8503401360544217,
  0.7653061224489796,
  0.7891156462585034,
  0.8333333333333334]}
```

- Let's fing out the best k value according to the accuracy values on the original datatset

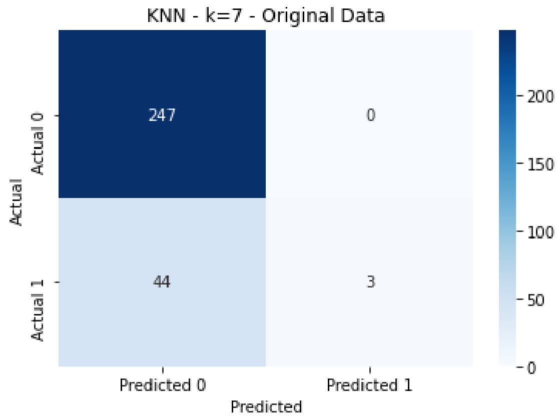
In [88]:

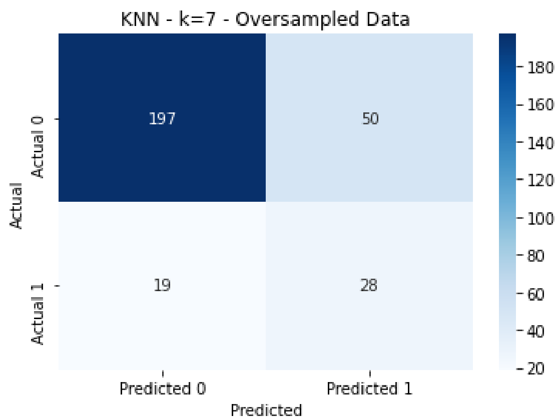
```
plt.figure(figsize=(10, 6))
plt.plot(k_val, acc_val, marker='o', linestyle='-', color='b')

plt.xlabel('Number of Neighbors (k)')
plt.ylabel('Accuracy')
plt.title('KNN: Accuracy vs. Number of Neighbors (k)')

# Show the plot
plt.grid(True)
plt.ylim(0, 1.0)
plt.show()
```

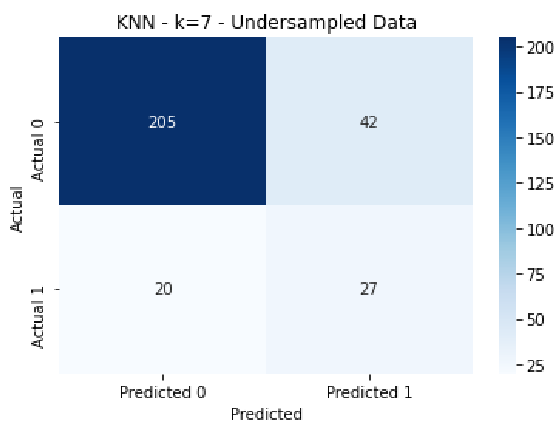


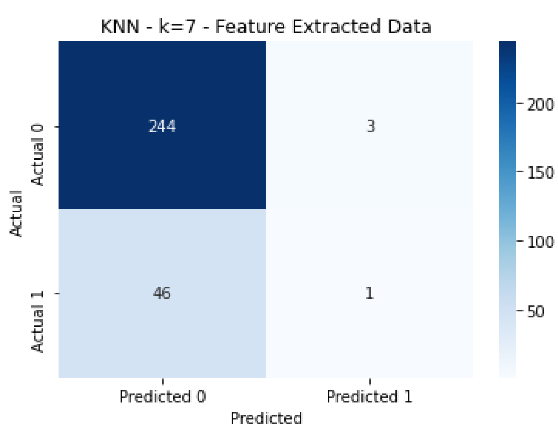
- Highest acuuracy is given when k = 7

In [89]:
```
conf_matrix(labels, "KNN - k=7")
```

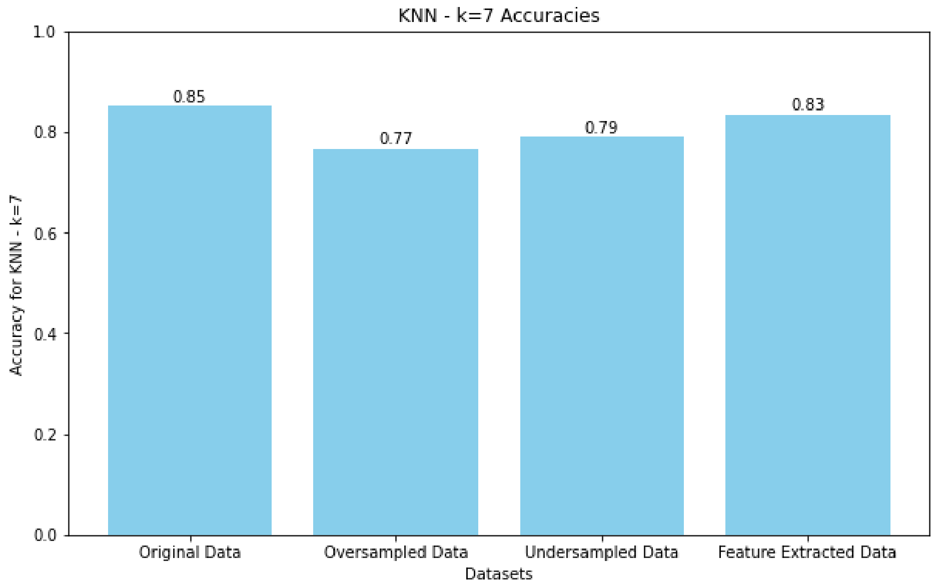








In [90]:
```
accu_plot(accus, "KNN - k=7")
```



7. Simple ANN

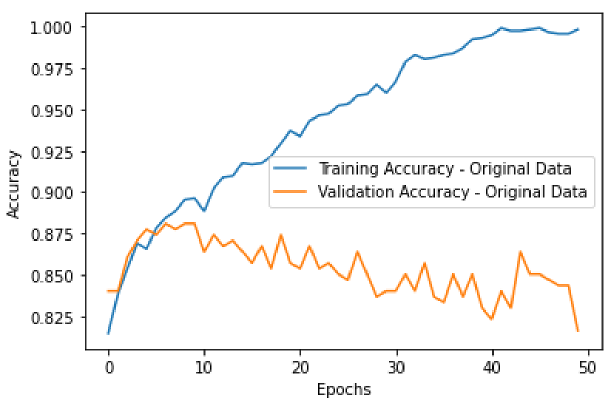
In [91]:
```
model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(64, activation='relu'),
    Dense(16, activation='relu'),
    Dense(1, activation='sigmoid')
])

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 128)               3968

 dense_1 (Dense)             (None, 64)                8256

 dense_2 (Dense)             (None, 16)                1040

 dense_3 (Dense)             (None, 1)                 17

=================================================================
Total params: 13,281
Trainable params: 13,281
Non-trainable params: 0
_________________________________________________________________
```

In [92]:
```
history1 = model.fit(X_train, y_train, epochs=50, batch_size=32, validation_data=(X_test,y_test))
```

```
Epoch 30/50
37/37 [==============================] - 0s 3ms/step - loss: 0.1138 - accuracy: 0.9600 - val_loss: 0.
5600 - val_accuracy: 0.8401
Epoch 31/50
37/37 [==============================] - 0s 3ms/step - loss: 0.1027 - accuracy: 0.9668 - val_loss: 0.
5463 - val_accuracy: 0.8401
Epoch 32/50
37/37 [==============================] - 0s 3ms/step - loss: 0.0809 - accuracy: 0.9787 - val_loss: 0.
5706 - val_accuracy: 0.8503
Epoch 33/50
37/37 [==============================] - 0s 3ms/step - loss: 0.0698 - accuracy: 0.9830 - val_loss: 0.
5995 - val_accuracy: 0.8401
Epoch 34/50
37/37 [==============================] - 0s 3ms/step - loss: 0.0724 - accuracy: 0.9804 - val_loss: 0.
6199 - val_accuracy: 0.8571
Epoch 35/50
37/37 [==============================] - 0s 3ms/step - loss: 0.0676 - accuracy: 0.9813 - val_loss: 0.
6281 - val_accuracy: 0.8367
Epoch 36/50
37/37 [==============================] - 0s 2ms/step - loss: 0.0643 - accuracy: 0.9830 - val_loss: 0.
```

In [93]:
```
plt.plot(history1.history['accuracy'], label='Training Accuracy - Original Data')
plt.plot(history1.history['val_accuracy'], label='Validation Accuracy - Original Data')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Evaluate the model and print final accuracy
y_pred = (model.predict(X_test) > 0.5).astype("int32").reshape(-1)
accuracy1_ann = accuracy_score(y_test, y_pred)
print("Accuracy : ", accuracy1_ann)
```




```
10/10 [==============================] - 0s 279us/step
Accuracy :  0.8163265306122449
```

In [94]:
```
model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train_ro.shape[1],)),
    Dense(64, activation='relu'),
    Dense(16, activation='relu'),
    Dense(1, activation='sigmoid')
])

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

model.summary()
```

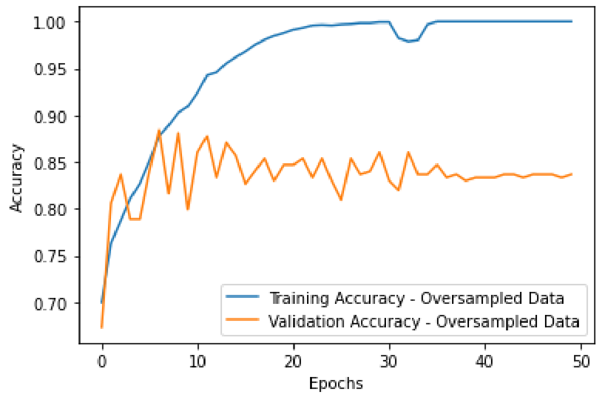
```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_4 (Dense)             (None, 128)               3968

 dense_5 (Dense)             (None, 64)                8256

 dense_6 (Dense)             (None, 16)                1040

 dense_7 (Dense)             (None, 1)                 17

=================================================================
Total params: 13,281
Trainable params: 13,281
Non-trainable params: 0
_________________________________________________________________
```

In [95]:
```
history2 = model.fit(X_train_ro, y_train_ro, epochs=50, batch_size=32, validation_data=(X_test,y_test))
```

```
62/62 [==============================] - 0s 2ms/step - loss: 0.0202 - accuracy: 0.9975 - val_loss: 0.
9031 - val_accuracy: 0.8537
Epoch 28/50
62/62 [==============================] - 0s 3ms/step - loss: 0.0154 - accuracy: 0.9985 - val_loss: 0.
9165 - val_accuracy: 0.8367
Epoch 29/50
62/62 [==============================] - 0s 3ms/step - loss: 0.0128 - accuracy: 0.9985 - val_loss: 0.
9434 - val_accuracy: 0.8401
Epoch 30/50
62/62 [==============================] - 0s 2ms/step - loss: 0.0085 - accuracy: 0.9995 - val_loss: 0.
9976 - val_accuracy: 0.8605
Epoch 31/50
62/62 [==============================] - 0s 2ms/step - loss: 0.0072 - accuracy: 0.9995 - val_loss: 1.
0197 - val_accuracy: 0.8299
Epoch 32/50
62/62 [==============================] - 0s 2ms/step - loss: 0.0468 - accuracy: 0.9823 - val_loss: 0.
9770 - val_accuracy: 0.8197
Epoch 33/50
62/62 [==============================] - 0s 2ms/step - loss: 0.0577 - accuracy: 0.9787 - val_loss: 0.
9975 - val_accuracy: 0.8605
```

In [96]:

```
plt.plot(history2.history['accuracy'], label='Training Accuracy - Oversampled Data')
plt.plot(history2.history['val_accuracy'], label='Validation Accuracy - Oversampled Data')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Evaluate the model and print final accuracy
y_pred_ro = (model.predict(X_test) > 0.5).astype("int32").reshape(-1)
accuracy2_ann = accuracy_score(y_test, y_pred_ro)
print("Accuracy : ", accuracy2_ann)
```




```
10/10 [==============================] - 0s 1ms/step
Accuracy :  0.8367346938775511
```

In [106]:

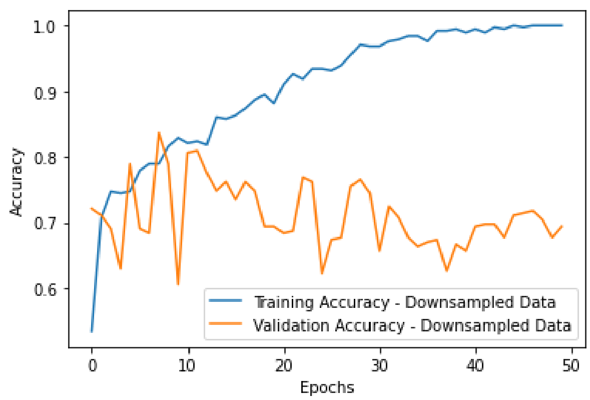
```
model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train_ru.shape[1],)),
    Dense(64, activation='relu'),
    Dense(16, activation='relu'),
    Dense(1, activation='sigmoid')
])

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_16 (Dense)            (None, 128)               3968

 dense_17 (Dense)            (None, 64)                8256

 dense_18 (Dense)            (None, 16)                1040

 dense_19 (Dense)            (None, 1)                 17

=================================================================
Total params: 13,281
Trainable params: 13,281
Non-trainable params: 0
_________________________________________________________________
```

In [107]:
```
history3 = model.fit(X_train_ru, y_train_ru, epochs=50, batch_size=32, validation_data=(X_test,y_test))
```

```
12/12 [==============================] - 0s 5ms/step - loss: 0.6277 - accuracy: 0.7079 - val_loss: 0.
5978 - val_accuracy: 0.7109
Epoch 3/50
12/12 [==============================] - 0s 4ms/step - loss: 0.5804 - accuracy: 0.7474 - val_loss: 0.
5921 - val_accuracy: 0.6905
Epoch 4/50
12/12 [==============================] - 0s 4ms/step - loss: 0.5540 - accuracy: 0.7447 - val_loss: 0.
6477 - val_accuracy: 0.6293
Epoch 5/50
12/12 [==============================] - 0s 5ms/step - loss: 0.5230 - accuracy: 0.7474 - val_loss: 0.
4686 - val_accuracy: 0.7891
Epoch 6/50
12/12 [==============================] - 0s 5ms/step - loss: 0.5016 - accuracy: 0.7789 - val_loss: 0.
5809 - val_accuracy: 0.6905
Epoch 7/50
12/12 [==============================] - 0s 4ms/step - loss: 0.4834 - accuracy: 0.7895 - val_loss: 0.
6055 - val_accuracy: 0.6837
Epoch 8/50
12/12 [==============================] - 0s 5ms/step - loss: 0.4623 - accuracy: 0.7895 - val_loss: 0.
3945 - val_accuracy: 0.8367
```

In [108]:
```
plt.plot(history3.history['accuracy'], label='Training Accuracy - Downsampled Data')
plt.plot(history3.history['val_accuracy'], label='Validation Accuracy - Downsampled Data')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Evaluate the model and print final accuracy
y_pred_ru = (model.predict(X_test) > 0.5).astype("int32").reshape(-1)
accuracy3_ann = accuracy_score(y_test, y_pred_ru)
print("Accuracy : ", accuracy3_ann)
```




```
10/10 [==============================] - 0s 942us/step
Accuracy :  0.6938775510204082
```

In [109]:

```
model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train_pca.shape[1],)),
    Dense(64, activation='relu'),
    Dense(16, activation='relu'),
    Dense(1, activation='sigmoid')
])

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

model.summary()
```

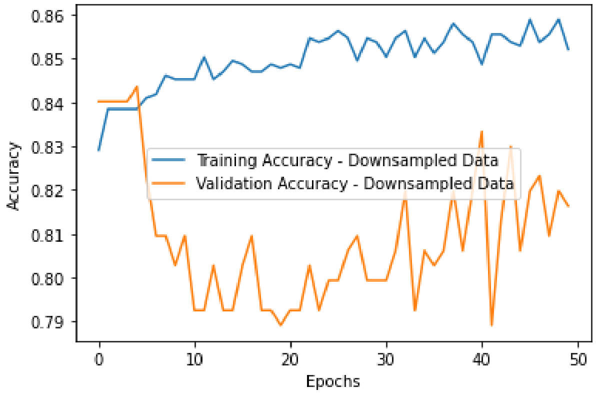
```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_20 (Dense)            (None, 128)               384

 dense_21 (Dense)            (None, 64)                8256

 dense_22 (Dense)            (None, 16)                1040

 dense_23 (Dense)            (None, 1)                 17

=================================================================
Total params: 9,697
Trainable params: 9,697
Non-trainable params: 0
_________________________________________________________________
```

In [110]:

```
history4 = model.fit(X_train_pca, y_train, epochs=50, batch_size=32, validation_data=(X_test_pca, y_test)
```

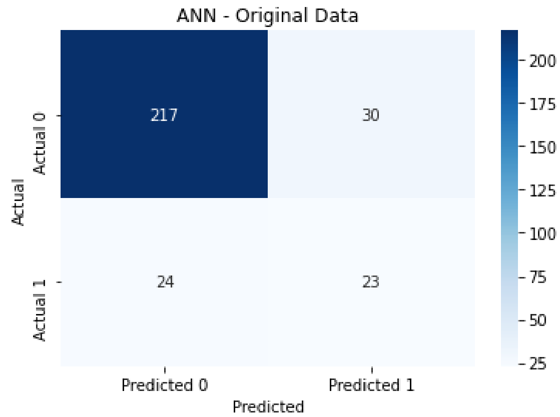
```
37/37 [==============================] - 0s 2ms/step - loss: 0.3990 - accuracy: 0.8401 - val_loss: 0.
4714 - val_accuracy: 0.7925
Epoch 10/50
37/37 [==============================] - 0s 2ms/step - loss: 0.3949 - accuracy: 0.8495 - val_loss: 0.
4667 - val_accuracy: 0.7891
Epoch 11/50
37/37 [==============================] - 0s 2ms/step - loss: 0.3941 - accuracy: 0.8452 - val_loss: 0.
4749 - val_accuracy: 0.7925
Epoch 12/50
37/37 [==============================] - 0s 2ms/step - loss: 0.3929 - accuracy: 0.8503 - val_loss: 0.
4741 - val_accuracy: 0.7925
Epoch 13/50
37/37 [==============================] - 0s 3ms/step - loss: 0.3913 - accuracy: 0.8537 - val_loss: 0.
4611 - val_accuracy: 0.7959
Epoch 14/50
37/37 [==============================] - 0s 3ms/step - loss: 0.3920 - accuracy: 0.8452 - val_loss: 0.
4948 - val_accuracy: 0.7925
Epoch 15/50
37/37 [==============================] - 0s 3ms/step - loss: 0.3916 - accuracy: 0.8495 - val_loss: 0.
4726 - val_accuracy: 0.8027
```

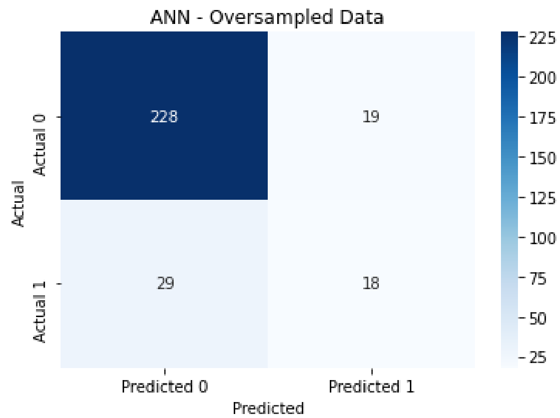
In [102]:
```
plt.plot(history4.history['accuracy'], label='Training Accuracy - Downsampled Data')
plt.plot(history4.history['val_accuracy'], label='Validation Accuracy - Downsampled Data')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Evaluate the model and print final accuracy
y_pred_pca = (model.predict(X_test_pca) > 0.5).astype("int32").reshape(-1)
accuracy4_ann = accuracy_score(y_test, y_pred_pca)
print("Accuracy : ", accuracy4_ann)
```

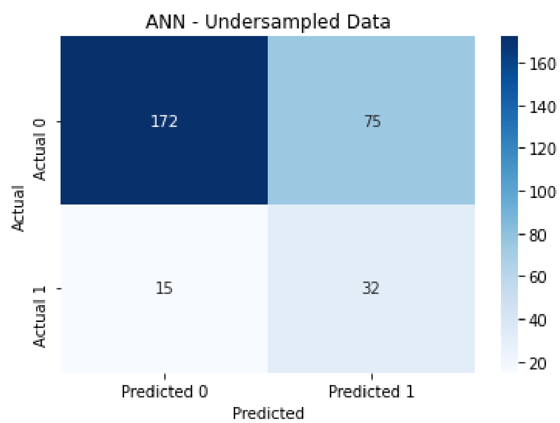


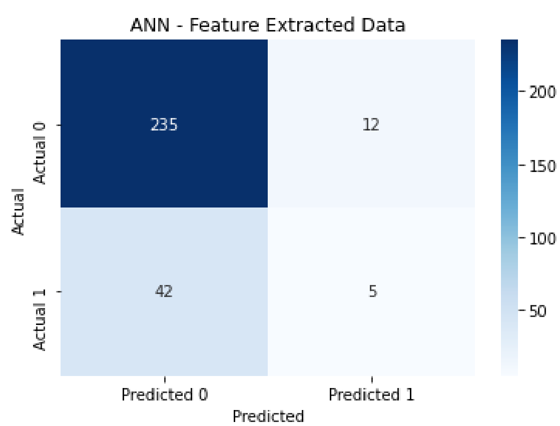

```
10/10 [==============================] - 0s 2ms/step
Accuracy :  0.8163265306122449
```

In [111]:
```
conf_matrix([(y_test, y_pred),(y_test, y_pred_ro),(y_test, y_pred_ru),(y_test, y_pred_pca)], "ANN")
```

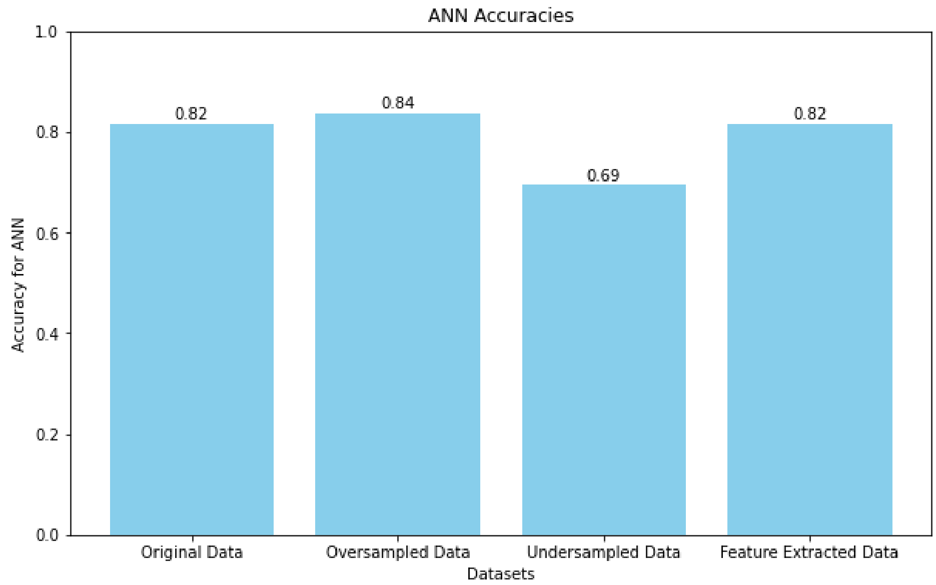








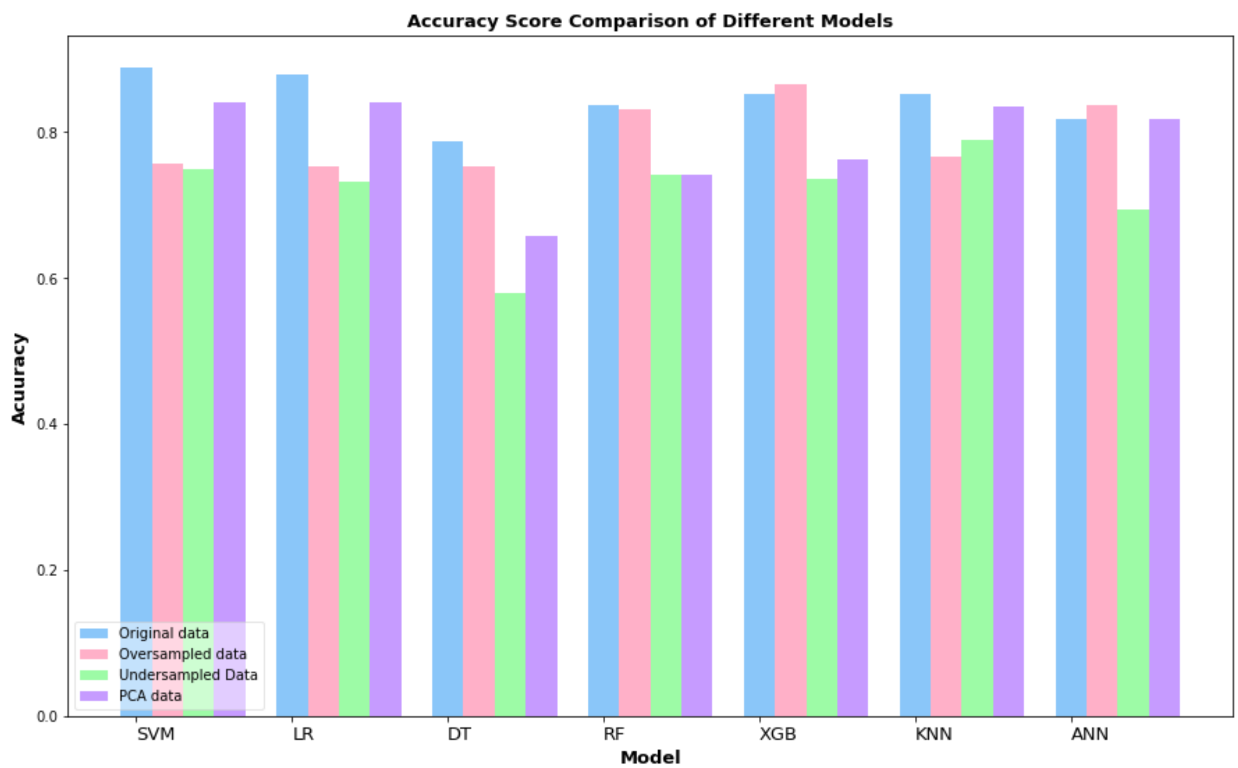
In [112]:
```
accu_plot([accuracy1_ann, accuracy2_ann, accuracy3_ann, accuracy4_ann], "ANN")
```



Model Comparison

- We will seperately compare accuracy values that we have already obtained.

In [113]:
```
colors = ['#8AC6F9', '#FFB0C8', '#9DFBA6', '#C69BFF']
accuracy = [[accuracy1_svm, accuracy2_svm, accuracy3_svm, accuracy4_svm],
           [accuracy1_lr, accuracy2_lr, accuracy3_lr, accuracy4_lr],
           [accuracy1_dt, accuracy2_dt, accuracy3_dt, accuracy4_dt],
           [accuracy1_rf, accuracy2_rf, accuracy3_rf, accuracy4_rf],
           [accuracy1_xg, accuracy2_xg, accuracy3_xg, accuracy4_xg],
           accus,
           [accuracy1_ann, accuracy2_ann, accuracy3_ann, accuracy4_ann]]
accuracy = np.array(accuracy)


classi = ['SVM', 'LR', 'DT', 'RF', 'XGB', 'KNN', 'ANN']
models = ['Original data', 'Oversampled data', 'Undersampled Data', 'PCA data']

# Step 3: Create a bar chart using plt.bar() function
x = np.arange(len(classi))
width = 0.2  # the width of the bars

fig, ax = plt.subplots(figsize=(15, 9))

for i in range(len(models)):
    ax.bar(x + i * width, accuracy[:, i], width, label=models[i], color=colors[i])

# Step 4: Customize the chart
ax.set_title('Accuracy Score Comparison of Different Models', fontweight='bold', fontsize=13)
ax.set_xlabel('Model', fontweight='bold', fontsize=13)
ax.set_ylabel('Acuuracy', fontweight='bold', fontsize=13)
ax.set_xticks(x)
ax.set_xticklabels(classi, ha='left', fontsize=13)
ax.legend(framealpha=0.5, fontsize=10, loc='lower left')

plt.show()
```



Conclusion

- We can identify two major issues with the dataset.
  1. Lesser number of overall samples.
  2. Imbalanced class problem is appearing.

- We have tried two sampling techniques oversampling and undersampling. Even though both the techniques are not on to the mark when considering the accuracy they obtained training 7 different models, it can be noticed that they predict both the classes without any bias compared to original dataset.
- We have tried PCA with 2 principal components, but the original dataset worked better with the classification models.
- It can be noticed that SVM classifier gives the highest accuracy with respect to the original dataset.
- Overall, ANN seems to be more accurate except for undersampled dataset and gives quiet good accuracies for all the datasets.