Introduction

In the world of insurance, understanding your customers and their needs is crucial for success. My client, an insurance company, has provided health insurance to its customers and is now seeking to expand its offerings to include vehicle insurance. To do so, they need to identify which of their policyholders from the past year would also be interested in this new type of insurance.

As a data scientist, I have been tasked to build a model that predicts which customers are likely to be interested in vehicle insurance based on their demographic information, vehicle details, policy data, and more. This will enable my client to tailor their marketing strategies and better serve their customers while optimizing their revenue.

Libraries

Importing necessary libraries and packages

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import make_scorer, roc_auc_score, accuracy_score, precision_score,reca
f1_score,confusion_matrix,ConfusionMatrixDisplay
from sklearn.utils import class_weight
from sklearn.model_selection import GridSearchCV

import warnings
warnings.filterwarnings("ignore")
```

Data Importing & Preprocessing

Loading the data and preparing it for machine learning

```
#mounting my google drive
from google.colab import drive
drive.mount("/content/drive/")
```

```
Mounted at /content/drive/
```

```
#loading the train data
vehInsuranceTrain = pd.read_csv("/content/sample_data/train.csv")
```

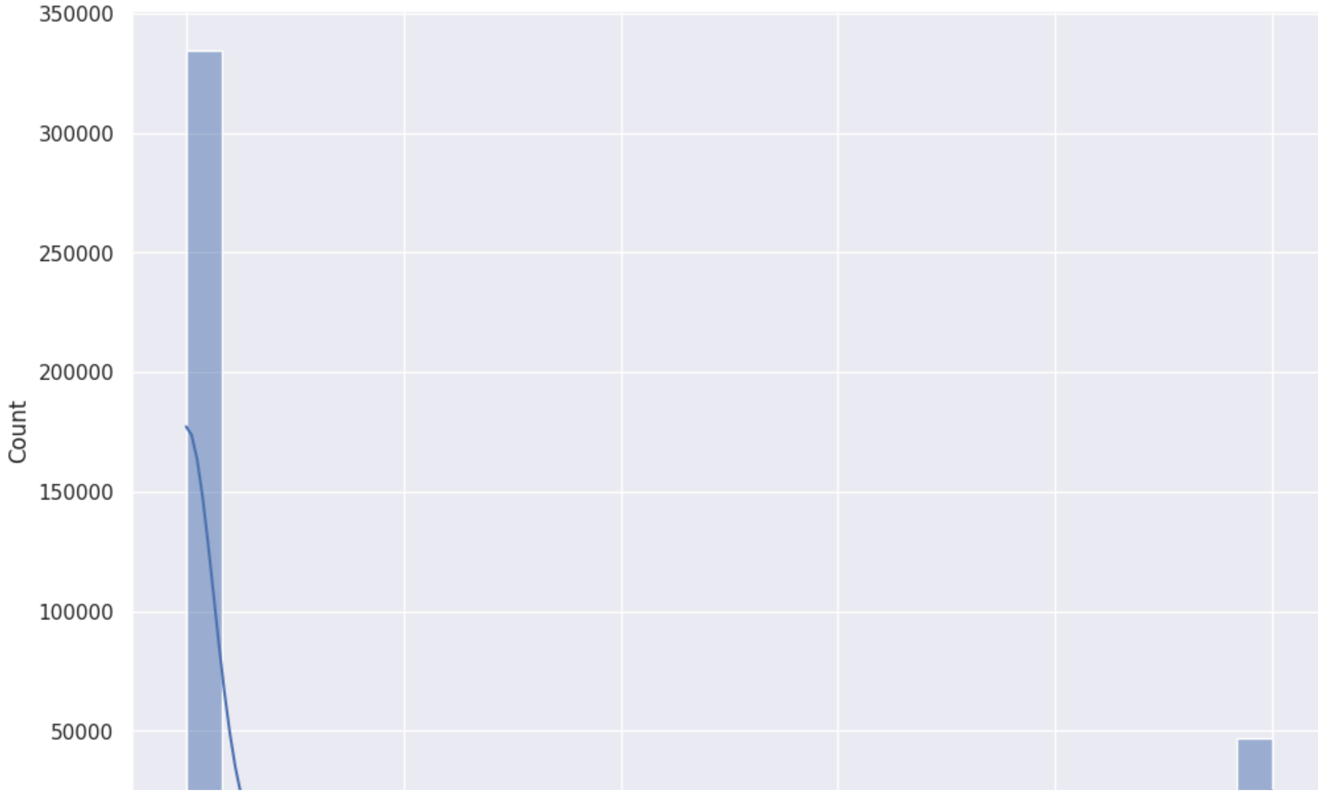
```
#inspecting the shape of the data
vehInsuranceTrain.shape
```

```
(381109, 12)
```

```
vehInsuranceTrain.head()
```

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Age	Vehic
0	1	Male	44	1	28.0	0	> 2 Years	
1	2	Male	76	1	3.0	0	1-2 Year	
2	3	Male	47	1	28.0	0	> 2 Years	
3	4	Male	21	1	11.0	1	< 1 Year	
4	5	Female	29	1	41.0	1	< 1 Year	

```
#inspecting the distribution of the target variable
sns.set(rc={'figure.figsize': (11.7, 8.28)})
sns.histplot(data=vehInsuranceTrain, x="Response", bins=30, kde="True")
plt.show()
```




```
#checking the unique counts of the target variable
vehInsuranceTrain["Response"].value_counts()
```

```
0    334399
1     46710
Name: Response, dtype: int64
```

```
#defining a dictionary to map the numerical values of the target varaible to the class name
#Class 0 is Not_Interested and Class 1 is Interested
classNames = {0: "Not_Interested", 1: "Interested"}
```

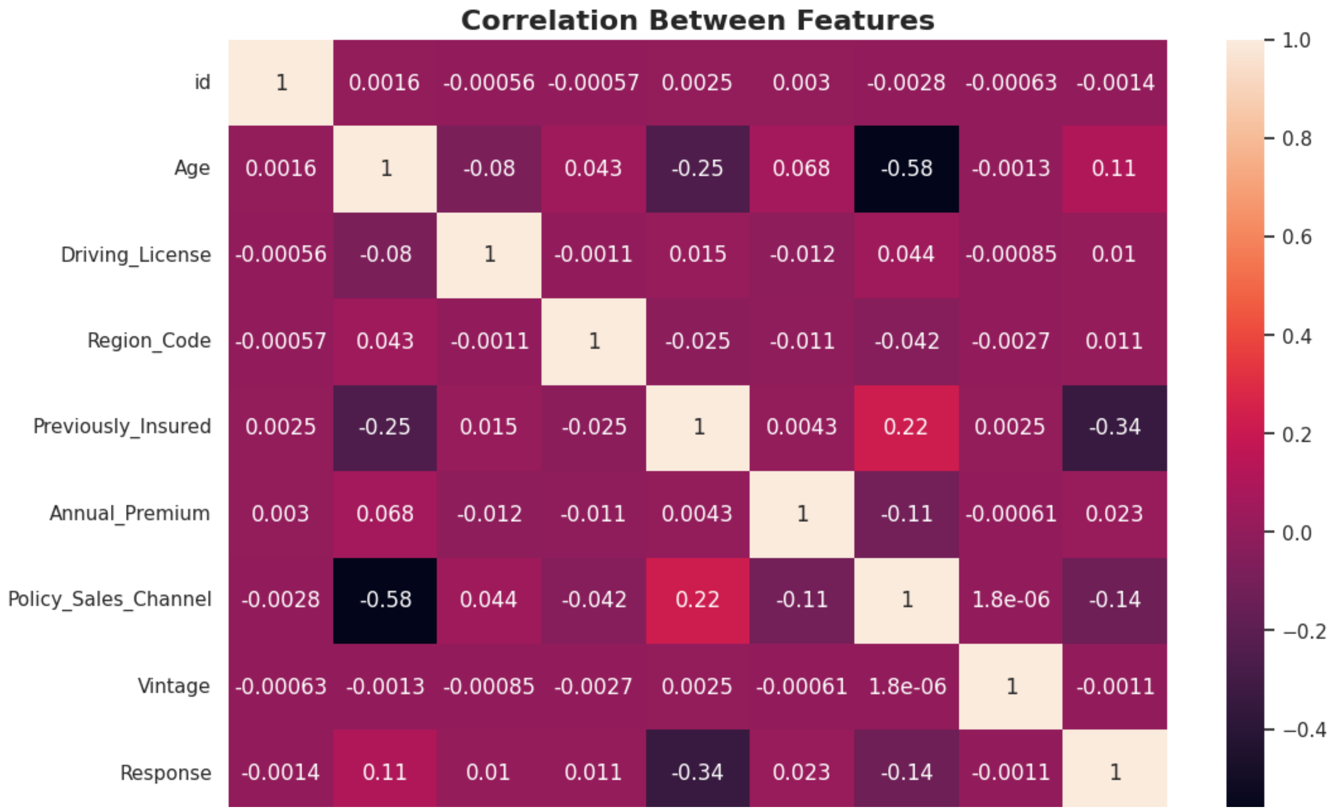
```
#Checking to see there are no missing values
vehInsuranceTrain.isna().sum()
```

```
id                      0
Gender                  0
Age                     0
Driving_License         0
Region_Code             0
Previously_Insured      0
Vehicle_Age             0
Vehicle_Damage          0
Annual_Premium          0
Policy_Sales_Channel    0
Vintage                 0
Response                0
dtype: int64
```

```
#checking correlation among variables with the target variable
corr = vehInsuranceTrain.corr()
corr
```

	id	Age	Driving_License	Region_Code	Previously_Insur
id	1.000000	0.001561	-0.000564	-0.000572	0.0024
Age	0.001561	1.000000	-0.079782	0.042574	-0.2546
Driving_License	-0.000564	-0.079782	1.000000	-0.001081	0.0149
Region_Code	-0.000572	0.042574	-0.001081	1.000000	-0.0246
Previously_Insured	0.002457	-0.254682	0.014969	-0.024659	1.0000
Annual_Premium	0.003027	0.067507	-0.011906	-0.010588	0.0042
Policy_Sales_Channel	-0.002837	-0.577826	0.043731	-0.042420	0.2193
Vintage	-0.000630	-0.001264	-0.000848	-0.002750	0.0025
Response	-0.001368	0.111147	0.010155	0.010570	-0.3411

```
#plotting a heatmap of correlation matrix
plt.figure(figsize=(12, 8))
sns.heatmap(data=corr, annot=True)
plt.title("Correlation Between Features", fontsize=16, fontweight="bold")
plt.show()
```




```
#instantiating the label encoder
labelEncoder = LabelEncoder()

#applying LabelEncoder to the categorical columns of the train data
vehInsuranceTrain["Gender"] = labelEncoder.fit_transform(vehInsuranceTrain["Gender"])
vehInsuranceTrain["Vehicle_Age"] = labelEncoder.fit_transform(vehInsuranceTrain["Vehicle_Age
vehInsuranceTrain["Vehicle_Damage"] = labelEncoder.fit_transform(vehInsuranceTrain["Vehicle_


#checking to see changes have been made
vehInsuranceTrain.head()
```

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Age	Vehic
0	1	1	44	1	28.0	0	2	
1	2	1	76	1	3.0	0	0	
2	3	1	47	1	28.0	0	2	
3	4	1	21	1	11.0	1	1	
4	5	0	29	1	41.0	1	1	

```
#loading the test data
vehInsuranceTest = pd.read_csv("/content/sample_data/test.csv")
vehInsuranceTest.head()
```

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Age	V
0	381110	Male	25	1	11.0	1	< 1 Year	
1	381111	Male	40	1	28.0	0	1-2 Year	
2	381112	Male	47	1	28.0	0	1-2 Year	
3	381113	Male	24	1	27.0	1	< 1 Year	

```
#inspecting the shape of the test data
vehInsuranceTest.shape
```

```
(127037, 11)
```

```
#checking to see if any missing values in the test data
vehInsuranceTest.isna().sum()
```

```
id                      0
Gender                  0
Age                     0
Driving_License         0
Region_Code             0
Previously_Insured      0
Vehicle_Age             0
Vehicle_Damage          0
Annual_Premium          0
Policy_Sales_Channel    0
Vintage                 0
dtype: int64
```

```
#applying LabelEncoder to the categorical columns of the test data
vehInsuranceTest["Gender"] = labelEncoder.fit_transform(vehInsuranceTest["Gender"])
vehInsuranceTest["Vehicle_Age"] = labelEncoder.fit_transform(vehInsuranceTest["Vehicle_Age"]
vehInsuranceTest["Vehicle_Damage"] = labelEncoder.fit_transform(vehInsuranceTest["Vehicle_Da
```

```
#checking to see changes have been made in the test data
vehInsuranceTest.head()
```

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Age	V
0	381110	1	25	1	11.0	1	1	
1	381111	1	40	1	28.0	0	0	
2	381112	1	47	1	28.0	0	0	
3	381113	1	24	1	27.0	1	1	
4	381114	1	27	1	28.0	1	1	

```
#splitting the train data into features and target variables
X = vehInsuranceTrain.drop("Response", axis=1)
y = vehInsuranceTrain["Response"]


#splitting the features and target variables into train and validation sets
X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.2, random_state=25)


#scaling the features applying standard scaler
scaler = StandardScaler()

#applying the scaler to the X_train, X_valid
X_train = scaler.fit_transform(X_train)
X_valid = scaler.transform(X_valid)

#applying the scaler to the test data
X_test = vehInsuranceTest
X_test = scaler.transform(X_test)


#inspecting the shape of the split data
display(X_train.shape, X_valid.shape, y_train.shape, y_valid.shape)
```

```
(304887, 11)
(76222, 11)
(304887,)
(76222,)
```

Hyperparameters Tuning

Training the models with different hyperparameters and checking for the best hyperparameters to build the models with.

DecisionTreeClassifier

```
#creating an instance of the DecisionTreeClassifier
dTree = DecisionTreeClassifier()

#defining the hyperparameters to be tuned
param_grid = {
    'class_weight': [None, {0: 1, 1: 2}, {0: 1, 1: 3}, {0: 1, 1: 4}, {0: 1, 1: 5}],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt', 'log2', None]
}

#creating the scoring function
scoring = {'AUC': make_scorer(roc_auc_score),
           'accuracy': 'accuracy',
           'precision': 'precision',
           'recall': 'recall',
           'f1': 'f1'}

#creating a GridSearchCV object with the DecisionTreeClassifier and the hyperparameter grid
grid_search = GridSearchCV(dTree, param_grid, cv=5, scoring=scoring, n_jobs=-1, refit="AUC")

#fitting the GridSearchCV object to the training data
grid_search.fit(X_train, y_train)
```

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

```
#printing the best hyperparameters and the corresponding score
print("Best Hyperparameters:", grid_search.best_params_)
print("Best Score:", grid_search.best_score_)
```

```
Best Hyperparameters: {'class_weight': {0: 1, 1: 5}, 'max_features': 'sqrt', 'min_sample
Best Score: 0.6930306015451573
```

```
print(grid_search.cv_results_.keys())
```

```
dict_keys(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_time', 'param_
```

```
#getting the indices of the sorted mean_test_score array in descending order
sorted_indices = np.argsort(grid_search.cv_results_['mean_test_AUC'])[::-1]

# loop through the sorted indices to find the next best parameters
for i in sorted_indices:
    if grid_search.cv_results_['params'][i] != grid_search.best_params_:
        print("Next Best Hyperparameters:", grid_search.cv_results_['params'][i])
        print("Next Best Score:", grid_search.cv_results_['mean_test_AUC'][i])
        break
```

```
Next Best Hyperparameters: {'class_weight': {0: 1, 1: 5}, 'max_features': 'sqrt', 'min_s
Next Best Score: 0.6919820845648952
```

Logistic Regression

```
#creating an instance of the log reg
logReg = LogisticRegression()

#defining the hyperparameters to be tuned
param_grid = {'penalty': ['l2', 'l1'],
              'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000],
              'class_weight': [None, 'balanced']}

#defining the scoring function with AUC and F1 metrics
scoring = {
    'AUC': make_scorer(roc_auc_score),
    'accuracy': 'accuracy',
    'precision': 'precision',
    'recall': 'recall',
    'F1': 'f1'
}

#creating a GridSearchCV object with the SVM classifier and the hyperparameter grid
grid_search = GridSearchCV(logReg, param_grid, cv=5, scoring=scoring, n_jobs=-1, refit="AUC'

#fitting the GridSearchCV object to the training data
grid_search.fit(X_train, y_train)
```

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

```
# print the best hyperparameters and the corresponding score
print("Best Hyperparameters:", grid_search.best_params_)
print("Best Score:", grid_search.best_score_)
```

```
Best Hyperparameters: {'C': 0.1, 'class_weight': 'balanced', 'penalty': 'l2'}
Best Score: 0.7839449889053152
```

```
# getting the indices of the sorted mean_test_score array in descending order
sorted_indices = np.argsort(grid_search.cv_results_['mean_test_AUC'])[::-1]

# loop through the sorted indices to find the next best parameters
for i in sorted_indices:
    if grid_search.cv_results_['params'][i] != grid_search.best_params_:
        next_score = grid_search.cv_results_['mean_test_AUC'][i]
        if not np.isnan(next_score):
            print("Next Best Hyperparameters:", grid_search.cv_results_['params'][i])
            print("Next Best Score:", next_score)
            break
```

```
Next Best Hyperparameters: {'C': 10, 'class_weight': 'balanced', 'penalty': 'l2'}
Next Best Score: 0.7839449889053152
```

I performed hyperparameter tuning for two classification models, the decision tree classifier and logistic regression. For the decision tree classifier, I found the best hyperparameters to be a class weight of {0:1, 1:5}, max features of 'sqrt', min samples leaf of 4, and min samples split of 5 with a best score of 0.693. The next best parameters were very similar to the best parameters, with min samples split of 2 and a slightly lower score of 0.692.

For logistic regression, I found the best hyperparameters to be a regularization parameter (C) of 0.1, penalty of 'l2', and class weight of 'balanced' with a best score of 0.784. The next best parameters had a higher regularization parameter of 10 and the same penalty and class weight with an identical score of 0.784.

Overall, hyperparameter tuning is a crucial step in optimizing model performance and achieving the best possible accuracy. The results of mu analysis provide valuable insights into the best hyperparameters for the decision tree and logistic regression models. These best hyperparameters will be used to build and train the models for higher accuracy.

Model Building & Development

Building and training the models with the hyperparameters chosen in the previous step

Decision Tree Classifier

```
dTree1 = DecisionTreeClassifier(class_weight={0: 1, 1: 5}, max_features='log2', min_samples_
dTree2 = DecisionTreeClassifier(class_weight={0: 1, 1: 5}, max_features='log2', min_samples_


dTree1.fit(X_train, y_train)
dTree2.fit(X_train, y_train)
```

```
DecisionTreeClassifier

DecisionTreeClassifier(class_weight={0: 1, 1: 5}, max_features='log2',
                       min_samples_leaf=4, random_state=23)
```

```
dTreePred1 = dTree1.predict(X_valid)
dTreePred2 = dTree2.predict(X_valid)


print(dTreePred1)
print(dTreePred2)
```

```
[0 0 0 ... 0 1 1]
[0 0 0 ... 0 1 1]
```

Sample Decision Tree Classifier Predictions

```
#Will the client be interested or not?
#getting index of y_valid sample
sample_index = np.where(y_valid == y_valid[212381])[0][0]

#getting the corresponding X_test sample
X_test_sample = X_test[sample_index].reshape(1, -1)

#making prediction
dTreePredict1 = dTree1.predict(X_test_sample)

#converting prediction to class name
className = classNames[dTreePredict1[0]]

print(y_valid[212381])
print(className)
```

```
1
Interested
```

```
#Will the client be interested or not?

#getting index of y_valid sample
sample_index = np.where(y_valid == y_valid[316194])[0][0]

#getting the corresponding X_test sample
X_test_sample = X_test[sample_index].reshape(1, -1)

#making prediction
dTreePredict2 = dTree2.predict(X_test_sample)

#converting prediction to class name
className = classNames[dTreePredict2[0]]

print(y_valid[316194])
print(className)
```

```
0
Not_Interested
```

Logistic Regression

```
logReg1 = LogisticRegression(C=0.1, class_weight="balanced", penalty="l2", random_state=23)
logReg2 = LogisticRegression(C=10, class_weight="balanced", penalty="l2", random_state=23)
```

```
logReg1.fit(X_train, y_train)
logReg2.fit(X_train, y_train)
```

```
LogisticRegression
LogisticRegression(C=10, class_weight='balanced', random_state=23)
```

```
logRegPred1 = logReg1.predict(X_valid)
logRegPred2 = logReg2.predict(X_valid)
```

```
print(logRegPred1)
print(logRegPred2)
```

```
[0 0 1 ... 1 1 1]
[0 0 1 ... 1 1 1]
```

Sample Logistic Regression Predictions

```
#Will the client be interested or not?
#getting index of y_valid sample
sample_index = np.where(y_valid == y_valid[212381])[0][0]

#getting the corresponding X_test sample
X_test_sample = X_test[sample_index].reshape(1, -1)

#making prediction
logRegPredict1 = logReg1.predict(X_test_sample)

#converting prediction to class name
className = classNames[logRegPredict1[0]]

print(y_valid[212381])
print(className)
```

```
1
Interested
```

```
#getting index of y_valid sample
sample_index = np.where(y_valid == y_valid[78824])[0][0]

#getting the corresponding X_test sample
X_test_sample = X_test[sample_index].reshape(1, -1)

#making prediction
logRegPredict2 = logReg2.predict(X_test_sample)

#converting prediction to class name
className = classNames[logRegPredict2[0]]

print(y_valid[78824])
print(className)
```

```
0
Not_Interested
```

Evaluation

Evaluating the performance of the different models on the test data using various metrics such as roc-auc, accuracy, precision, recall, f1 scores, and confusion matrix.

ROC-AUC

```
#Evaluating the decision tree classifiers
print("Decision Tree 1 Classifier AUC:", roc_auc_score(y_valid, dTreePred1))
print("Decision Tree 2 Classifier AUC:", roc_auc_score(y_valid, dTreePred2))
```

```
Decision Tree 1 Classifier AUC: 0.6966293955507357
Decision Tree 2 Classifier AUC: 0.6966293955507357
```

```
print("Logistic Regression AUC:", roc_auc_score(y_valid, logRegPred1))
print("Logistic Regression AUC:", roc_auc_score(y_valid, logRegPred2))
```

```
Logistic Regression AUC: 0.7852206736895498
Logistic Regression AUC: 0.7852206736895498
```

Accuracy

```
print("Decision Tree Accuracy:", accuracy_score(y_valid, dTreePred1))
print("Decision Tree Accuracy:", accuracy_score(y_valid, dTreePred2))
```

```
Decision Tree Accuracy: 0.7642412951641259
Decision Tree Accuracy: 0.7642412951641259
```

```
print("Logistic Regression Accuracy:", accuracy_score(y_valid, logRegPred1))
print("Logistic Regression Accuracy:", accuracy_score(y_valid, logRegPred2))
```

```
Logistic Regression Accuracy: 0.6402744614415785
Logistic Regression Accuracy: 0.6402744614415785
```

Precision

```
print("Decision Tree 1 Classifier Precision:", precision_score(y_valid, dTreePred1))
print("Decision Tree 2 Classifier Precision:", precision_score(y_valid, dTreePred2))
```

```
Decision Tree 1 Classifier Precision: 0.28443398588093927
Decision Tree 2 Classifier Precision: 0.28443398588093927
```

```
print("Logistic Regression 1 Precision:", precision_score(y_valid, logRegPred1))
print("Logistic Regression 2 Precision:", precision_score(y_valid, logRegPred2))
```

```
Logistic Regression 1 Precision: 0.2516091764317544
Logistic Regression 2 Precision: 0.2516091764317544
```

Recall

```
print("Decision Tree 1 Classifier Recall_score:", recall_score(y_valid, dTreePred1))
print("Decision Tree 2 Classifier Recall_score:", recall_score(y_valid, dTreePred2))
```

```
Decision Tree 1 Classifier Recall_score: 0.6070092958649428
Decision Tree 2 Classifier Recall_score: 0.6070092958649428
```

```
print("Logistic Regression 1  Recall_score:", recall_score(y_valid, dTreePred1))
print("Logistic Regression 2 Recall_score:", recall_score(y_valid, dTreePred2))
```

```
Logistic Regression 1  Recall_score: 0.6070092958649428
Logistic Regression 2 Recall_score: 0.6070092958649428
```

F1_score

```
print("Decision Tree 1 Classifier F1_Score:", f1_score(y_valid, dTreePred1))
print("Decision Tree 2 Classifier F1_score:", f1_score(y_valid, dTreePred2))
```

```
Decision Tree 1 Classifier F1_Score: 0.3873585162961953
Decision Tree 2 Classifier F1_score: 0.3873585162961953
```

```
print("Logistic Regression 1 F1_Score:", f1_score(y_valid, logRegPred1))
print("Logistic Regression 1 F1_score:", f1_score(y_valid, logRegPred2))
```

```
Logistic Regression 1 F1_Score: 0.40019250541421475
Logistic Regression 1 F1_score: 0.40019250541421475
```

Confusion Matrix

```
dTree1_cm =confusion_matrix(y_valid, dTreePred1)
dTree2_cm =confusion_matrix(y_valid, dTreePred2)
```

```
display(dTree1_cm, dTree2_cm)
```

```
array([[52571, 14292],
       [ 3678,  5681]])
array([[52571, 14292],
       [ 3678,  5681]])
```

```
log1_cm = confusion_matrix(y_valid, logRegPred1)
log2_cm = confusion_matrix(y_valid, logRegPred2)
```

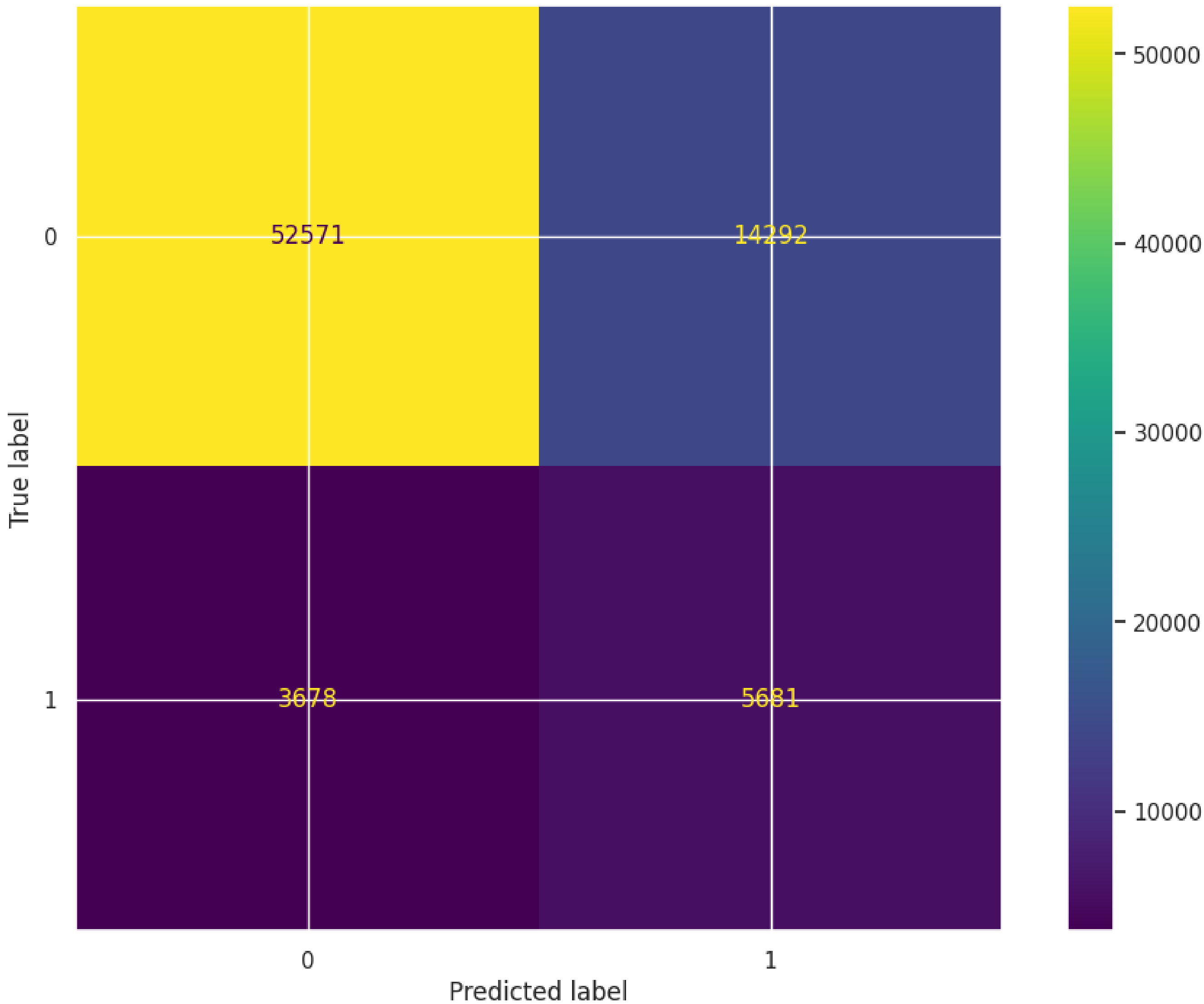
```
display(log1_cm, log2_cm)
```

```
array([[39656, 27207],
       [  212,  9147]])
array([[39656, 27207],
       [  212,  9147]])
```

Confusion Matrix Display

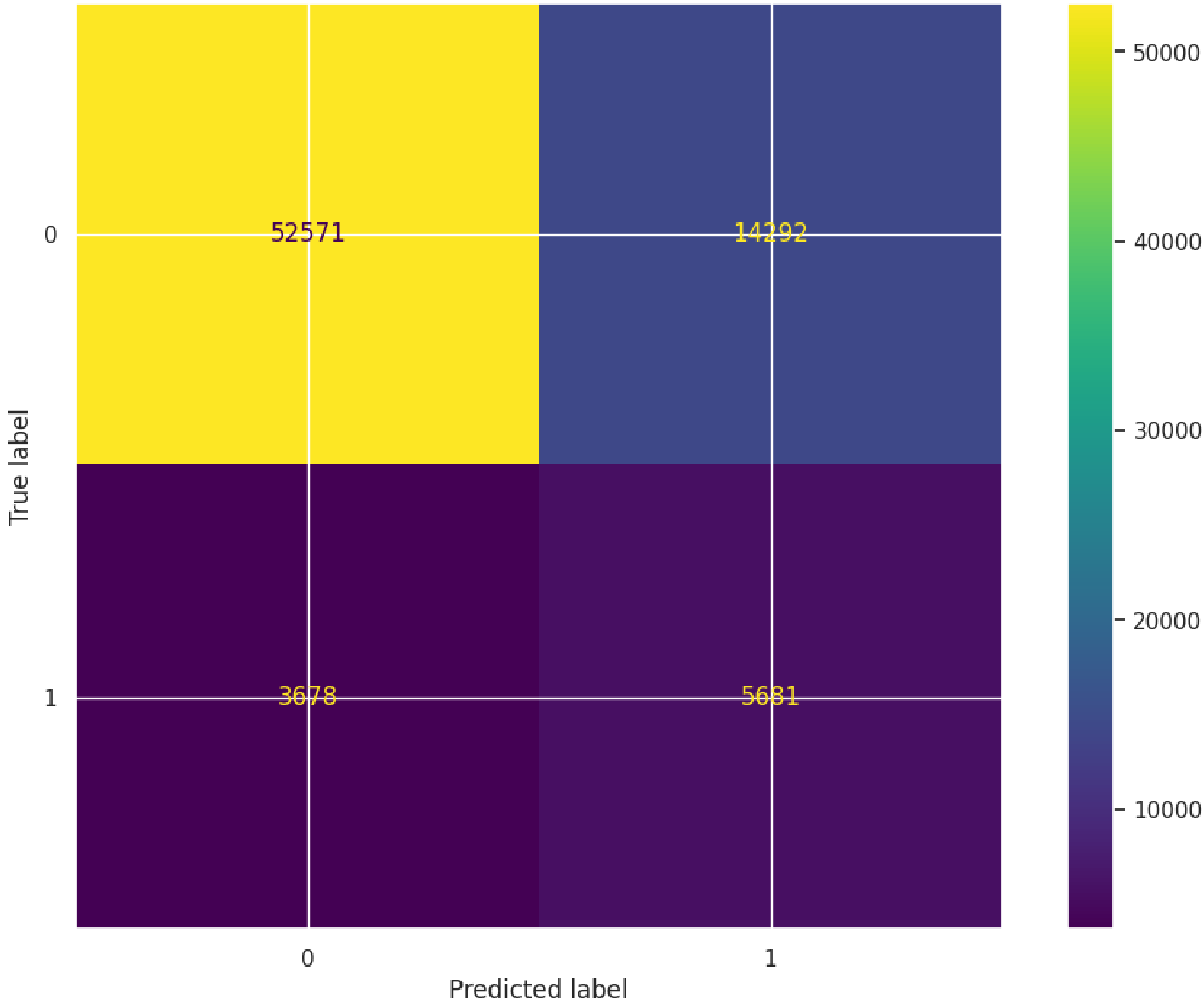
```
ConfusionMatrixDisplay(dTree1_cm).plot()
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f038d77e280>
```



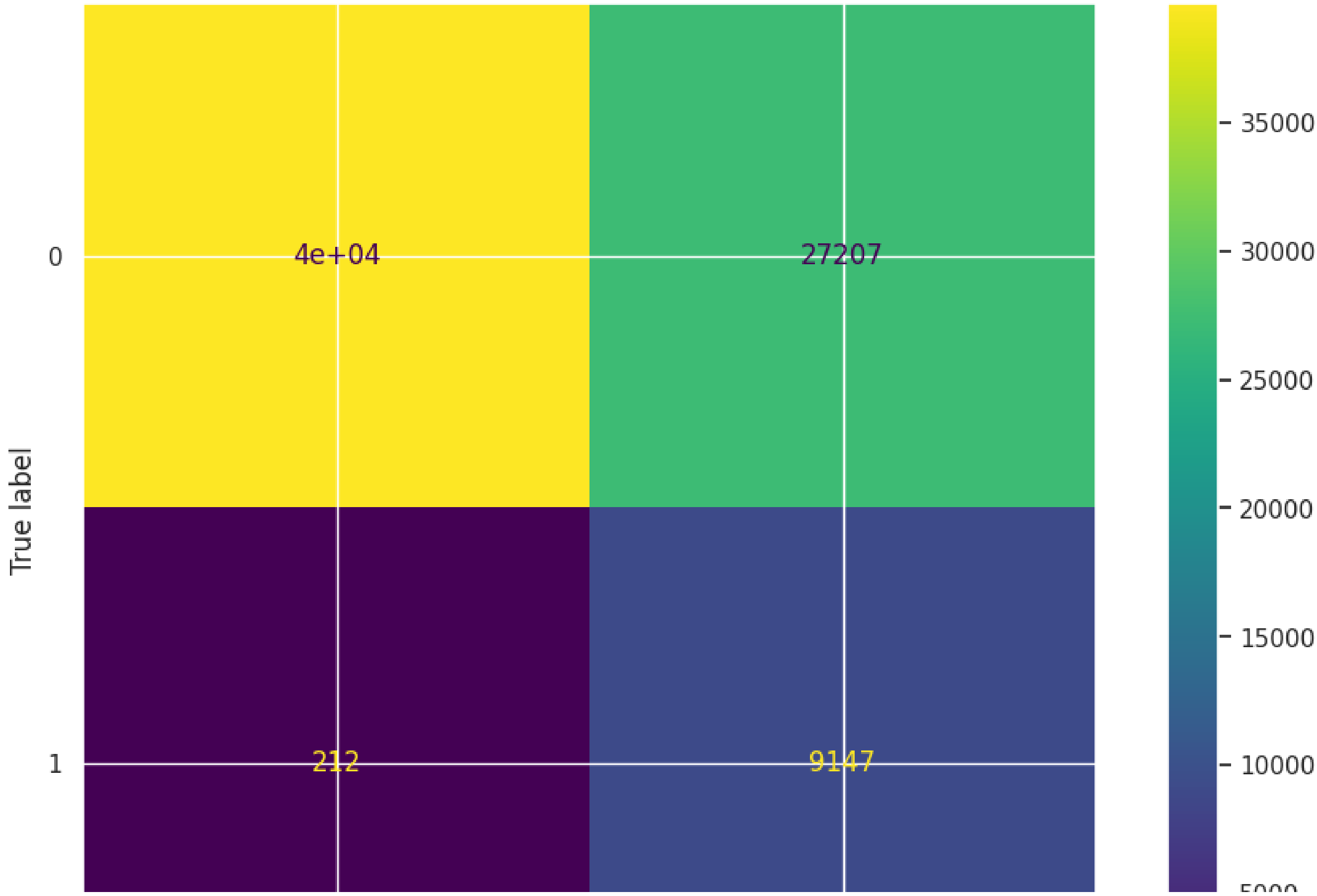

```
ConfusionMatrixDisplay(dTree2_cm).plot()
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f0382b36d00>
```



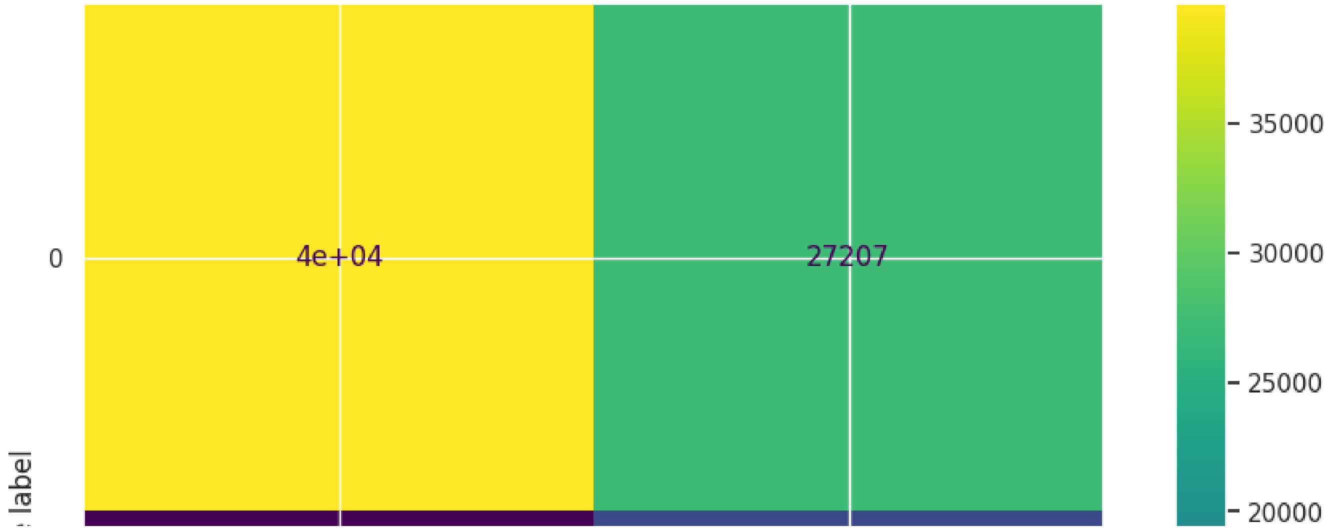

```
ConfusionMatrixDisplay(log1_cm).plot()
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f038d77edf0>
```




```
ConfusionMatrixDisplay(log2_cm).plot()
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f038d77eac0>
```



Summary

In this project, I was tasked with building a model that predicts which customers of an insurance company would be interested in purchasing vehicle insurance. I used demographic information, vehicle details, and policy data as features to build and train the models.

Before building the models, I performed hyperparameter tuning on both the decision tree and logistic regression classifiers. The best and next best parameters obtained from the hyperparameter tuning were used to build and train the models. I evaluated the models using different metrics, focusing on the AUC metric due to class imbalance.

The decision tree classifiers had an AUC score of 0.6966293955507357, while the logistic regression classifier had an AUC score of 0.7839449889053152. The accuracy score for both