In [1]:

```
!pip3 install scikit-learn==1.3.2
!pip install imbalanced-learn==0.11.0
import pandas as pd
import numpy as np

%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.impute import SimpleImputer

from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler

from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import (
    AdaBoostClassifier,
    GradientBoostingClassifier,
    RandomForestClassifier,
    BaggingClassifier,
)
from xgboost import XGBClassifier

from sklearn import metrics
from sklearn.model_selection import train_test_split, StratifiedKFold, cro
from sklearn.metrics import (
    f1_score,
    accuracy_score,
    recall_score,
    precision_score,
    confusion_matrix,
    roc_auc_score,
    ConfusionMatrixDisplay,
)

from sklearn.preprocessing import StandardScaler, MinMaxScaler, OneHotEnco


from sklearn.model_selection import GridSearchCV, RandomizedSearchCV

from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer

pd.set_option("display.max_columns", None)

pd.set_option("display.float_format", lambda x: "%.3f" % x)


import warnings

warnings.filterwarnings("ignore")
```

```
Requirement already satisfied: scikit-learn==1.3.2 in c:\users\conne\anac
onda3\lib\site-packages (1.3.2)
Requirement already satisfied: numpy<2.0,>=1.17.3 in c:\users\conne\anaco
nda3\lib\site-packages (from scikit-learn==1.3.2) (1.24.3)
Requirement already satisfied: scipy>=1.5.0 in c:\users\conne\anaconda3\l
ib\site-packages (from scikit-learn==1.3.2) (1.10.1)
Requirement already satisfied: joblib>=1.1.1 in c:\users\conne\anaconda3
\lib\site-packages (from scikit-learn==1.3.2) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\conne\ana
conda3\lib\site-packages (from scikit-learn==1.3.2) (2.2.0)
Requirement already satisfied: imbalanced-learn==0.11.0 in c:\users\conne
\anaconda3\lib\site-packages (0.11.0)
Requirement already satisfied: numpy>=1.17.3 in c:\users\conne\anaconda3
\lib\site-packages (from imbalanced-learn==0.11.0) (1.24.3)
Requirement already satisfied: scipy>=1.5.0 in c:\users\conne\anaconda3\l
ib\site-packages (from imbalanced-learn==0.11.0) (1.10.1)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\conne\anac
onda3\lib\site-packages (from imbalanced-learn==0.11.0) (1.3.2)
Requirement already satisfied: joblib>=1.1.1 in c:\users\conne\anaconda3
\lib\site-packages (from imbalanced-learn==0.11.0) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\conne\ana
conda3\lib\site-packages (from imbalanced-learn==0.11.0) (2.2.0)
```

Here im importing all packages

In [2]:
```
df = pd.read_csv('/Users/conne/Downloads/Train.csv.csv')
df_test = pd.read_csv('/Users/conne/Downloads/Test.csv.csv')
```

Here im loading both sets of data

In [3]:
```
data = df.copy()
```

In [4]:
```
data_test = df_test.copy()
```

In [5]:
```
data.shape
```

Out[5]:
```
(20000, 41)
```

We can see the first set has 20000 rows and 41 columns

In [6]:
```
data_test.shape
```

Out[6]:
```
(5000, 41)
```

We can see the first set has 5000 rows and 41 columns

In [7]:
```
data.head()
```

Out[7]:

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
0	-4.465	-4.679	3.102	0.506	-0.221	-2.033	-2.911	0.051	-1.522	3.762	-5.715	0.736
1	3.366	3.653	0.910	-1.368	0.332	2.359	0.733	-4.332	0.566	-0.101	1.914	-0.951
2	-3.832	-5.824	0.634	-2.419	-1.774	1.017	-2.099	-3.173	-2.082	5.393	-0.771	1.107
3	1.618	1.888	7.046	-1.147	0.083	-1.530	0.207	-2.494	0.345	2.119	-3.053	0.460
4	-0.111	3.872	-3.758	-2.983	3.793	0.545	0.205	4.849	-1.855	-6.220	1.998	4.724

In [8]:
```
data.tail()
```

Out[8]:

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11
19995	-2.071	-1.088	-0.796	-3.012	-2.288	2.807	0.481	0.105	-0.587	-2.899	8.868
19996	2.890	2.483	5.644	0.937	-1.381	0.412	-1.593	-5.762	2.150	0.272	-2.095
19997	-3.897	-3.942	-0.351	-2.417	1.108	-1.528	-3.520	2.055	-0.234	-0.358	-3.782
19998	-3.187	-10.052	5.696	-4.370	-5.355	-1.873	-3.947	0.679	-2.389	5.457	1.583
19999	-2.687	1.961	6.137	2.600	2.657	-4.291	-2.344	0.974	-1.027	0.497	-9.589

In [9]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 41 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   V1      19982 non-null  float64
 1   V2      19982 non-null  float64
 2   V3      20000 non-null  float64
 3   V4      20000 non-null  float64
 4   V5      20000 non-null  float64
 5   V6      20000 non-null  float64
 6   V7      20000 non-null  float64
 7   V8      20000 non-null  float64
 8   V9      20000 non-null  float64
 9   V10     20000 non-null  float64
 10  V11     20000 non-null  float64
 11  V12     20000 non-null  float64
 12  V13     20000 non-null  float64
 13  V14     20000 non-null  float64
```

In [10]:
```
data.duplicated().sum()
```

Out[10]: 0

In [11]:

```python
data.isnull().sum()
```

Out[11]:

```
V1        18
V2        18
V3         0
V4         0
V5         0
V6         0
V7         0
V8         0
V9         0
V10        0
V11        0
V12        0
V13        0
V14        0
V15        0
V16        0
V17        0
V18        0
V19        0
V20        0
V21        0
V22        0
V23        0
V24        0
V25        0
V26        0
V27        0
V28        0
V29        0
V30        0
V31        0
V32        0
V33        0
V34        0
V35        0
V36        0
V37        0
V38        0
V39        0
V40        0
Target     0
dtype: int64
```

we have a couple null values that must be fixed

In [12]:
```
data_test.isnull().sum()
```

Out[12]:
```
V1     5
V2     6
V3     0
V4     0
V5     0
V6     0
V7     0
V8     0
V9     0
V10    0
V11    0
V12    0
V13    0
V14    0
V15    0
V16    0
V17    0
V18    0
V19    0
```

we have a couple null values that must be fixed

In [13]:
```
data.describe().T
```

Out[13]:

	count	mean	std	min	25%	50%	75%	max
V1	19982.000	-0.272	3.442	-11.876	-2.737	-0.748	1.840	15.493
V2	19982.000	0.440	3.151	-12.320	-1.641	0.472	2.544	13.089
V3	20000.000	2.485	3.389	-10.708	0.207	2.256	4.566	17.091
V4	20000.000	-0.083	3.432	-15.082	-2.348	-0.135	2.131	13.236
V5	20000.000	-0.054	2.105	-8.603	-1.536	-0.102	1.340	8.134
V6	20000.000	-0.995	2.041	-10.227	-2.347	-1.001	0.380	6.976
V7	20000.000	-0.879	1.762	-7.950	-2.031	-0.917	0.224	8.006
V8	20000.000	-0.548	3.296	-15.658	-2.643	-0.389	1.723	11.679
V9	20000.000	-0.017	2.161	-8.596	-1.495	-0.068	1.409	8.138
V10	20000.000	-0.013	2.193	-9.854	-1.411	0.101	1.477	8.108
V11	20000.000	-1.895	3.124	-14.832	-3.922	-1.921	0.119	11.826
V12	20000.000	1.605	2.930	-12.948	-0.397	1.508	3.571	15.081
V13	20000.000	1.580	2.875	-13.228	-0.224	1.637	3.460	15.420
V14	20000.000	-0.951	1.790	-7.739	-2.171	-0.957	0.271	5.671
V15	20000.000	-2.415	3.355	-16.417	-4.415	-2.383	-0.359	12.246
V16	20000.000	-2.925	4.222	-20.374	-5.634	-2.683	-0.095	13.583
V17	20000.000	-0.134	3.345	-14.091	-2.216	-0.015	2.069	16.756
V18	20000.000	1.189	2.592	-11.644	-0.404	0.883	2.572	13.180
V19	20000.000	1.182	3.397	-13.492	-1.050	1.279	3.493	13.238
V20	20000.000	0.024	3.669	-13.923	-2.433	0.033	2.512	16.052
V21	20000.000	-3.611	3.568	-17.956	-5.930	-3.533	-1.266	13.840
V22	20000.000	0.952	1.652	-10.122	-0.118	0.975	2.026	7.410
V23	20000.000	-0.366	4.032	-14.866	-3.099	-0.262	2.452	14.459
V24	20000.000	1.134	3.912	-16.387	-1.468	0.969	3.546	17.163
V25	20000.000	-0.002	2.017	-8.228	-1.365	0.025	1.397	8.223
V26	20000.000	1.874	3.435	-11.834	-0.338	1.951	4.130	16.836
V27	20000.000	-0.612	4.369	-14.905	-3.652	-0.885	2.189	17.560
V28	20000.000	-0.883	1.918	-9.269	-2.171	-0.891	0.376	6.528
V29	20000.000	-0.986	2.684	-12.579	-2.787	-1.176	0.630	10.722
V30	20000.000	-0.016	3.005	-14.796	-1.867	0.184	2.036	12.506
V31	20000.000	0.487	3.461	-13.723	-1.818	0.490	2.731	17.255
V32	20000.000	0.304	5.500	-19.877	-3.420	0.052	3.762	23.633
V33	20000.000	0.050	3.575	-16.898	-2.243	-0.066	2.255	16.692
V34	20000.000	-0.463	3.184	-17.985	-2.137	-0.255	1.437	14.358
V35	20000.000	2.230	2.937	-15.350	0.336	2.099	4.064	15.291
V36	20000.000	1.515	3.801	-14.833	-0.944	1.567	3.984	19.330

	count	mean	std	min	25%	50%	75%	max
V37	20000.000	0.011	1.788	-5.478	-1.256	-0.128	1.176	7.467
V38	20000.000	-0.344	3.948	-17.375	-2.988	-0.317	2.279	15.290
V39	20000.000	0.891	1.753	-6.439	-0.272	0.919	2.058	7.760
V40	20000.000	-0.876	3.012	-11.024	-2.940	-0.921	1.120	10.654
Target	20000.000	0.056	0.229	0.000	0.000	0.000	0.000	1.000

we can see the satistical summary

In [14]:

```
def histogram_boxplot(data, feature, figsize=(12, 7), kde=False, bins=None
    """
    Boxplot and histogram combined

    data: dataframe
    feature: dataframe column
    figsize: size of figure (default (12,7))
    kde: whether to the show density curve (default False)
    bins: number of bins for histogram (default None)
    """
    f2, (ax_box2, ax_hist2) = plt.subplots(
        nrows=2,  # Number of rows of the subplot grid= 2
        sharex=True,  # x-axis will be shared among all subplots
        gridspec_kw={"height_ratios": (0.25, 0.75)},
        figsize=figsize,
    )  # creating the 2 subplots
    sns.boxplot(
        data=data, x=feature, ax=ax_box2, showmeans=True, color="violet"
    )  # boxplot will be created and a star will indicate the mean value o
    sns.histplot(
        data=data, x=feature, kde=kde, ax=ax_hist2, bins=bins, palette="wi
    ) if bins else sns.histplot(
        data=data, x=feature, kde=kde, ax=ax_hist2
    )  # For histogram
    ax_hist2.axvline(
        data[feature].mean(), color="green", linestyle="--"
    )  # Add mean to the histogram
    ax_hist2.axvline(
        data[feature].median(), color="black", linestyle="-"
    )  # Add median to the histogram
```

Here i will preform univariant analysis

In [15]:

```
for feature in df.columns :
    histogram_boxplot(df, feature, figsize=(12,7), kde=False, bins=None)
```

. . .

We can see are data is fairly evenlly distributed

In [16]:
```
df["Target"].value_counts()
```

Out[16]:
```
0    18890
1     1110
Name: Target, dtype: int64
```

In [17]:
```
df_test["Target"].value_counts()
```

Out[17]:
```
0    4718
1     282
Name: Target, dtype: int64
```

Next I will preform prepare the data for model building

In [18]:
```
X = df.drop(["Target"], axis=1)
y = df["Target"]
```

In [19]:
```
X_train, X_val, y_train, y_val = train_test_split(
    X, y, test_size=0.25, random_state=1, stratify=y)
```

In [20]:
```
X_train.shape
```

Out[20]:
```
(15000, 40)
```

In [21]:
```
X_val.shape
```

Out[21]:
```
(5000, 40)
```

In [22]:
```
X_test = df_test.drop(["Target"], axis=1)
y_test = df_test["Target"]
```

In [23]:
```
X_test.shape
```

Out[23]:
```
(5000, 40)
```

In [24]:
```
imp_mode = SimpleImputer(strategy="median")

# fit and transform the imputer on train data
X_train = pd.DataFrame(imp_mode.fit_transform(X_train), columns=X_train.co

# Transform on validation and test data
X_val = pd.DataFrame(imp_mode.fit_transform(X_val), columns=X_train.column

# fit and transform the imputer on test data
X_test = pd.DataFrame(imp_mode.fit_transform(X_test), columns=X_train.colu
```

In [25]:

```
print(X_train.isna().sum())
print("-" * 30)
print(X_val.isna().sum())
print("-" * 30)
print(X_test.isna().sum())
```

```
V1     0
V2     0
V3     0
V4     0
V5     0
V6     0
V7     0
V8     0
V9     0
V10    0
V11    0
V12    0
V13    0
V14    0
V15    0
V16    0
V17    0
V18    0
V19    0
```

In [26]:

```
def model_performance_classification_sklearn(model, predictors, target):
    """
    Function to compute different metrics to check classification model pe

    model: classifier
    predictors: independent variables
    target: dependent variable
    """
    TP= confusion_matrix(target, model.predict(predictors))[1,1]
    FP= confusion_matrix(target, model.predict(predictors))[0,1]
    FN= confusion_matrix(target, model.predict(predictors))[1,0]

    pred = model.predict(predictors)

    acc = accuracy_score(target, pred)
    recall = recall_score(target, pred)
    precision = precision_score(target, pred)
    f1 = f1_score(target, pred)

    df_perf = pd.DataFrame(
        {
            "Accuracy": acc,
            "Recall": recall,
            "Precision": precision,
            "F1": f1,
        },
        index=[0],
    )

    return df_perf
```

In [27]:

```
def confusion_matrix_sklearn(model, predictors, target):
    """
    To plot the confusion_matrix with percentages

    model: classifier
    predictors: independent variables
    target: dependent variable
    """
    y_pred = model.predict(predictors)
    cm = confusion_matrix(target, y_pred)
    labels = np.asarray(
        [
            ["{0:0.0f}".format(item) + "\n{0:.2%}".format(item / cm.flatte
            for item in cm.flatten()
        ]
    ).reshape(2, 2)

    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=labels, fmt="")
    plt.ylabel("True label")
    plt.xlabel("Predicted label")
```

In [28]:

```
scorer = metrics.make_scorer(metrics.recall_score)
```

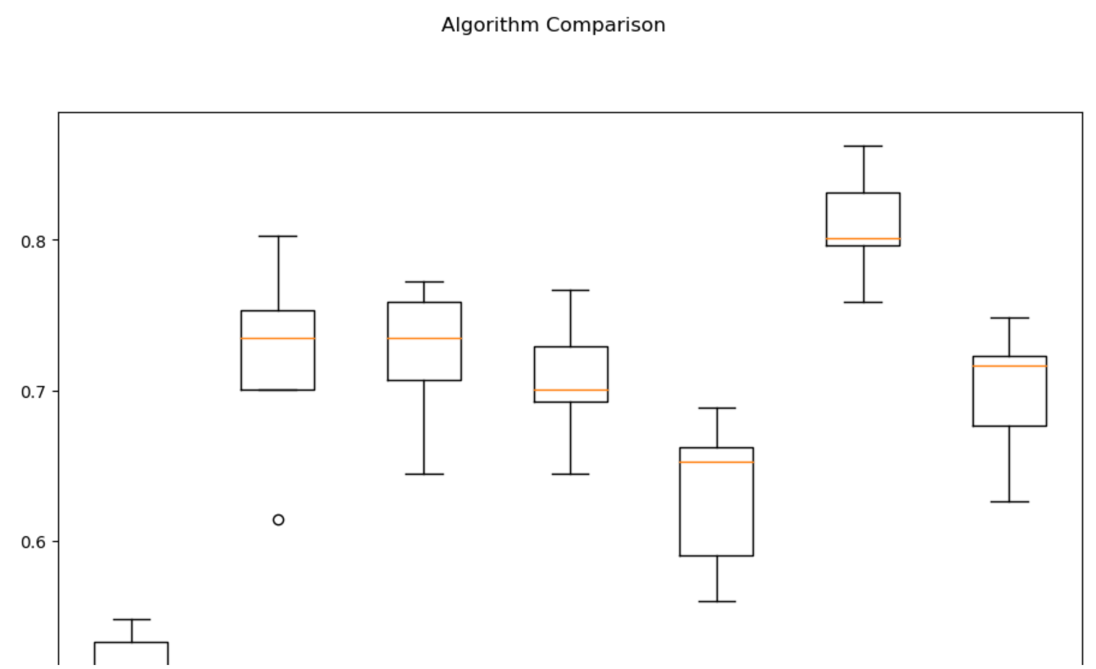
In [29]:

```
models = []

models.append(("Logistic regression", LogisticRegression(random_state=1)))
models.append(("Bagging", BaggingClassifier(random_state=1)))
models.append(("Random forest", RandomForestClassifier(random_state=1)))
models.append(("GBM", GradientBoostingClassifier(random_state=1)))
models.append(("Adaboost", AdaBoostClassifier(random_state=1)))
models.append(("Xgboost", XGBClassifier(random_state=1, eval_metric="loglo
models.append(("dtree", DecisionTreeClassifier(random_state=1)))

results = []
names = []

print("\n" "Cross-Validation Performance:" "\n")
for name, model in models:
    scoring = "recall"
    kfold = StratifiedKFold(
        n_splits=5, shuffle=True, random_state=1
    )
    cv_result = cross_val_score(
        estimator=model, X=X_train, y=y_train, scoring=scoring, cv=kfold
    )
    results.append(cv_result)
    names.append(name)
    print("{}: {}".format(name, cv_result.mean() * 100))

print("\n" "Validation Performance:" "\n")

for name, model in models:
    model.fit(X_train, y_train)
    scores = recall_score(y_val, model.predict(X_val))
    print("{}: {}".format(name, scores))
```

```
Cross-Validation Performance:

Logistic regression: 49.27566553639709
Bagging: 72.1080730106053
Random forest: 72.35192266070268
GBM: 70.66661857008873
Adaboost: 63.09140754635308
Xgboost: 81.00497799581561
dtree: 69.82829521679533

Validation Performance:

Logistic regression: 0.48201438848920863
Bagging: 0.7302158273381295
Random forest: 0.7266187050359713
GBM: 0.7230215827338129
Adaboost: 0.6762589928057554
Xgboost: 0.8309352517985612
dtree: 0.7050359712230215
```

In [30]:

```
fig = plt.figure(figsize=(11,8))

fig.suptitle("Algorithm Comparison")
ax = fig.add_subplot(111)

plt.boxplot(results)
ax.set_xticklabels(names)

plt.show()
```



In [ ]:

```
The best preforming model now was xgboost
```

In [31]:

```
print("Before UpSampling, counts of label 'Yes': {}".format(sum(y_train ==
print("Before UpSampling, counts of label 'No': {} \n".format(sum(y_train

sm = SMOTE(
    sampling_strategy=1, k_neighbors=5, random_state=1
)  # Synthetic Minority Over Sampling Technique
X_train_over, y_train_over = sm.fit_resample(X_train, y_train)


print("After UpSampling, counts of label 'Yes': {}".format(sum(y_train_ove
print("After UpSampling, counts of label 'No': {} \n".format(sum(y_train_o


print("After UpSampling, the shape of train_X: {}".format(X_train_over.sha
print("After UpSampling, the shape of train_y: {} \n".format(y_train_over.
```

```
Before UpSampling, counts of label 'Yes': 832
Before UpSampling, counts of label 'No': 14168

After UpSampling, counts of label 'Yes': 14168
After UpSampling, counts of label 'No': 14168

After UpSampling, the shape of train_X: (28336, 40)
After UpSampling, the shape of train_y: (28336,)
```

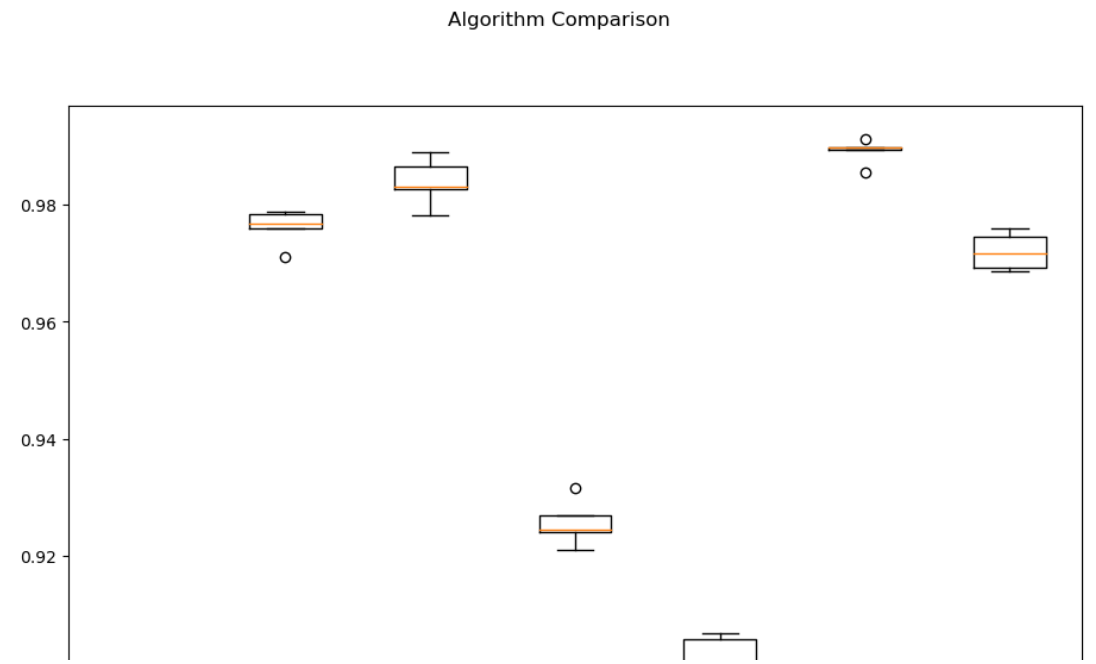
Next I will build my overfitting models

In [32]:

```
models = []

models.append(("Logistic regression", LogisticRegression(random_state=1)))
models.append(("Bagging", BaggingClassifier(random_state=1)))
models.append(("Random forest", RandomForestClassifier(random_state=1)))
models.append(("GBM", GradientBoostingClassifier(random_state=1)))
models.append(("Adaboost", AdaBoostClassifier(random_state=1)))
models.append(("Xgboost", XGBClassifier(random_state=1, eval_metric="loglo
models.append(("dtree", DecisionTreeClassifier(random_state=1)))

results = []
names = []

print("\n" "Cross-Validation Performance:" "\n")
for name, model in models:
    scoring = "recall"
    kfold = StratifiedKFold(
        n_splits=5, shuffle=True, random_state=1
    )
    cv_result = cross_val_score(
        estimator=model, X=X_train_over, y=y_train_over, scoring=scoring,
    )
    results.append(cv_result)
    names.append(name)
    print("{}: {}".format(name, cv_result.mean() * 100))

print("\n" "Validation Performance:" "\n")

for name, model in models:
    model.fit(X_train_over, y_train_over)
    scores = recall_score(y_val, model.predict(X_val))
    print("{}: {}".format(name, scores))
```

```
Cross-Validation Performance:

Logistic regression: 88.3963699328486
Bagging: 97.62141471581656
Random forest: 98.39075260047615
GBM: 92.56068151319724
Adaboost: 89.78689011775472
Xgboost: 98.91305241357217
dtree: 97.20494245534968

Validation Performance:

Logistic regression: 0.8489208633093526
Bagging: 0.8345323741007195
Random forest: 0.8489208633093526
GBM: 0.8776978417266187
Adaboost: 0.8561151079136691
Xgboost: 0.8669064748201439
dtree: 0.7769784172661871
```

In [33]:
```
fig = plt.figure(figsize=(11,8))

fig.suptitle("Algorithm Comparison")
ax = fig.add_subplot(111)

plt.boxplot(results)
ax.set_xticklabels(names)

plt.show()
```



My best preforming models now were adaboost and GBM

In [34]:
```
rus = RandomUnderSampler(random_state=1)
X_train_un, y_train_un = rus.fit_resample(X_train, y_train)
```

In [35]:
```
print("Before Under Sampling, counts of label 'Yes': {}".format(sum(y_trai
print("Before Under Sampling, counts of label 'No': {} \n".format(sum(y_tr

print("After Under Sampling, counts of label 'Yes': {}".format(sum(y_train
print("After Under Sampling, counts of label 'No': {} \n".format(sum(y_tra

print("After Under Sampling, the shape of train_X: {}".format(X_train_un.s
print("After Under Sampling, the shape of train_y: {} \n".format(y_train_u
```

```
Before Under Sampling, counts of label 'Yes': 832
Before Under Sampling, counts of label 'No': 14168

After Under Sampling, counts of label 'Yes': 832
After Under Sampling, counts of label 'No': 832

After Under Sampling, the shape of train_X: (1664, 40)
After Under Sampling, the shape of train_y: (1664,)
```

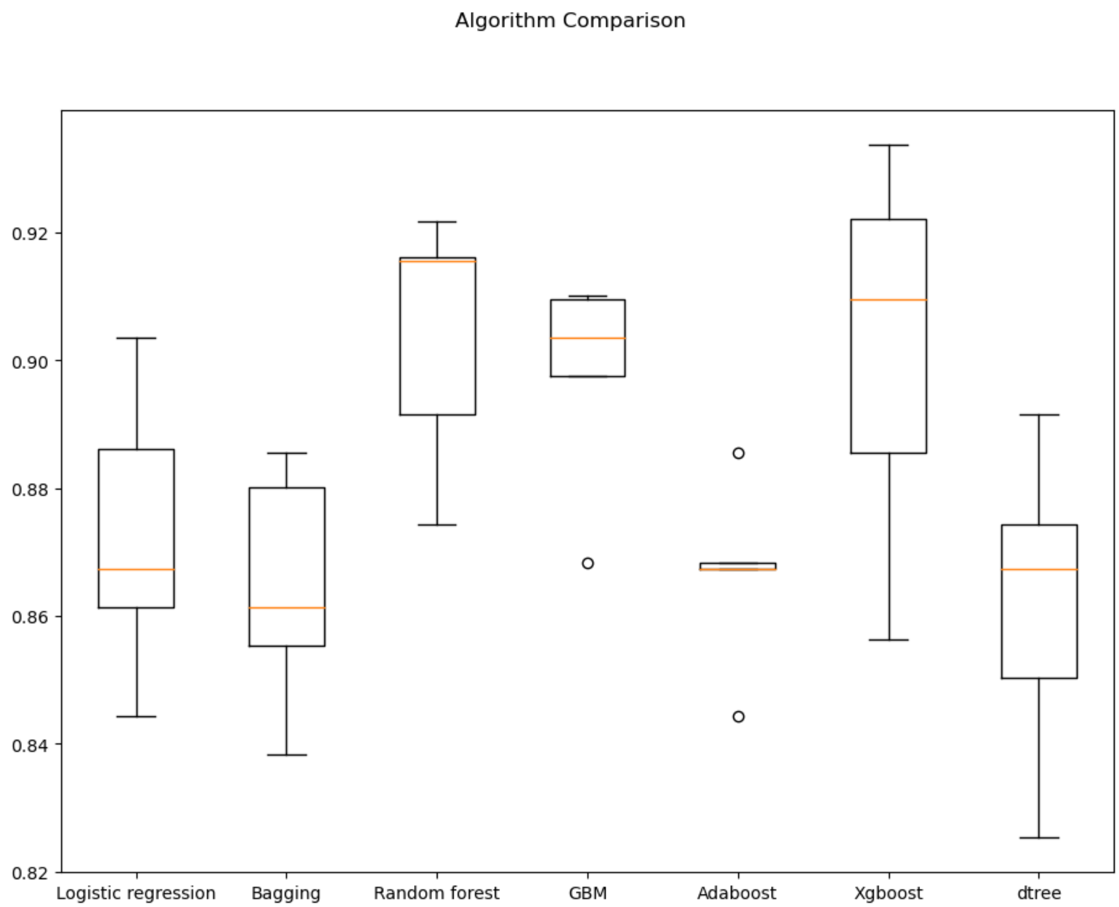
Next I will build my underfitting models

In [36]:

```
models = []

models.append(("Logistic regression", LogisticRegression(random_state=1)))
models.append(("Bagging", BaggingClassifier(random_state=1)))
models.append(("Random forest", RandomForestClassifier(random_state=1)))
models.append(("GBM", GradientBoostingClassifier(random_state=1)))
models.append(("Adaboost", AdaBoostClassifier(random_state=1)))
models.append(("Xgboost", XGBClassifier(random_state=1, eval_metric="loglo
models.append(("dtree", DecisionTreeClassifier(random_state=1)))

results = []
names = []

print("\n" "Cross-Validation Performance:" "\n")
for name, model in models:
    scoring = "recall"
    kfold = StratifiedKFold(
        n_splits=5, shuffle=True, random_state=1
    )
    cv_result = cross_val_score(
        estimator=model, X=X_train_un, y=y_train_un, scoring=scoring, cv=k
    )
    results.append(cv_result)
    names.append(name)
    print("{}: {}".format(name, cv_result.mean() * 100))

print("\n" "Validation Performance:" "\n")

for name, model in models:
    model.fit(X_train_un, y_train_un)
    scores = recall_score(y_val, model.predict(X_val))
    print("{}: {}".format(name, scores))
```

```
Cross-Validation Performance:

Logistic regression: 87.26138085275232
Bagging: 86.41945025611427
Random forest: 90.38669648654498
GBM: 89.78572974532861
Adaboost: 86.6611355602049
Xgboost: 90.14717552846115
dtree: 86.17776495202367

Validation Performance:

Logistic regression: 0.8525179856115108
Bagging: 0.8705035971223022
Random forest: 0.8920863309352518
GBM: 0.8884892086330936
Adaboost: 0.8489208633093526
Xgboost: 0.89568345323741
dtree: 0.841726618705036
```

In [37]:
```
fig = plt.figure(figsize=(11,8))

fig.suptitle("Algorithm Comparison")
ax = fig.add_subplot(111)

plt.boxplot(results)
ax.set_xticklabels(names)

plt.show()
```



My best preforming model was random forest

I will now tune my models

In [ ]:
```
%%time

#defining model
model = AdaBoostClassifier(random_state=1)

#Parameter grid to pass in RandomizedSearchCV
param_grid = {'n_estimators':[100,150,200],
            'learning_rate':[0.2,0.05],
            'base_estimator':[DecisionTreeClassifier(max_depth=1, random_s
           }


#Calling RandomizedSearchCV
Randomized_cv = RandomizedSearchCV(estimator=model, param_distributions=pa

#Fitting parameters in RandomizedSearchCV
Randomized_cv.fit(X_train_over,y_train_over)


print("Best parameters are {} with CV score={}:" .format(Randomized_cv.bes
```

In [39]:
```
tune_ada = AdaBoostClassifier(n_estimators= 200, learning_rate= 0.2, base_
tune_ada.fit(X_train_over,y_train_over)
```

Out[39]:
```
AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=3,
                                                         random_state=1),
                   learning_rate=0.2, n_estimators=200)
```

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In [40]:
```
ada_train_perf = model_performance_classification_sklearn(tune_ada,X_train
ada_train_perf
```

Out[40]:

	Accuracy	Recall	Precision	F1
0	0.992	0.988	0.995	0.992

In [41]:
```
ada_val_perf = model_performance_classification_sklearn(tune_ada,X_val,y_v
ada_val_perf
```

Out[41]:

	Accuracy	Recall	Precision	F1
0	0.979	0.849	0.789	0.818

In [42]:

```
model = RandomForestClassifier(random_state=1)

# Parameter grid to pass in RandomizedSearchCV
param_grid =  {'n_estimators':[200,250,300],
            'min_samples_leaf': np.arange(1,4),
            'max_features': [np.arange(0.3,0.6,0.1),'sqrt'],
               'max_samples':np.arange(0.4,0.7,0.1)
           }

# Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(
    estimator=model,
    param_distributions=param_grid,
    n_iter=50,
    n_jobs=-1,
    scoring=scorer,
    cv=5,
    random_state=1,
)

# Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train_un, y_train_un)

print(
    "Best parameters are {} with CV score={}:".format(
        randomized_cv.best_params_, randomized_cv.best_score_
    )
)
```

```
Best parameters are {'n_estimators': 300, 'min_samples_leaf': 2, 'max_sam
ples': 0.5, 'max_features': 'sqrt'} with CV score=0.8990116153235697:
```

In [43]:

```
tune_rf = RandomForestClassifier(n_estimators= 300, min_samples_leaf= 2, m
tune_rf.fit(X_train_un,y_train_un)
```

Out[43]:

```
RandomForestClassifier(max_samples=0.5, min_samples_leaf=2, n_estimators=
300)
```

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In [44]:

```
rf_train_perf = model_performance_classification_sklearn(tune_rf,X_train_u
rf_train_perf
```

Out[44]:

	Accuracy	Recall	Precision	F1
0	0.962	0.934	0.990	0.961

In [45]:
```
rf_val_perf = model_performance_classification_sklearn(tune_rf,X_val,y_val
rf_val_perf
```

Out[45]:

	Accuracy	Recall	Precision	F1
0	0.935	0.881	0.457	0.602

In [46]:
```
model = GradientBoostingClassifier(random_state=1)

# Parameter grid to pass in RandomizedSearchCV
param_grid =  {'n_estimators':[200,250,300],
            'learning_rate': np.arange(.05,.2,1),
            'max_features': np.arange(0.5,0.7),
               'subsample':np.arange(0.5,0.7)
           }

# Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(
    estimator=model,
    param_distributions=param_grid,
    n_iter=50,
    n_jobs=-1,
    scoring=scorer,
    cv=5,
    random_state=1,
)

# Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train_over, y_train_over)

print(
    "Best parameters are {} with CV score={}:".format(
        randomized_cv.best_params_, randomized_cv.best_score_
    )
)
```

```
Best parameters are {'subsample': 0.5, 'n_estimators': 300, 'max_feature
s': 0.5, 'learning_rate': 0.05} with CV score=0.9335123572593496:
```

In [47]:
```
tune_gb = GradientBoostingClassifier(n_estimators= 300, subsample= 0.5, le
tune_gb.fit(X_train_over, y_train_over)
```

Out[47]:
```
GradientBoostingClassifier(learning_rate=0.05, max_features=0.5,
                           n_estimators=300, subsample=0.5)
```

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In [48]:
```
gb_train_perf = model_performance_classification_sklearn(tune_gb,X_train_o
gb_train_perf
```

Out[48]:

	Accuracy	Recall	Precision	F1
0	0.960	0.937	0.981	0.959

In [49]:
```
gb_val_perf = model_performance_classification_sklearn(tune_gb,X_val,y_val
gb_val_perf
```

Out[49]:

	Accuracy	Recall	Precision	F1
0	0.971	0.878	0.683	0.769

In [50]:
```
models_train_comp_df = pd.concat(
    [
       gb_val_perf.T,
        rf_val_perf.T,
        ada_val_perf.T,
        ],
    axis=1,
)
models_train_comp_df.columns = [
    "Gradient Boosting",
    "Random Forest",
    "Ada",
]
print("Training performance comparison:")
models_train_comp_df
```

```
Training performance comparison:
```

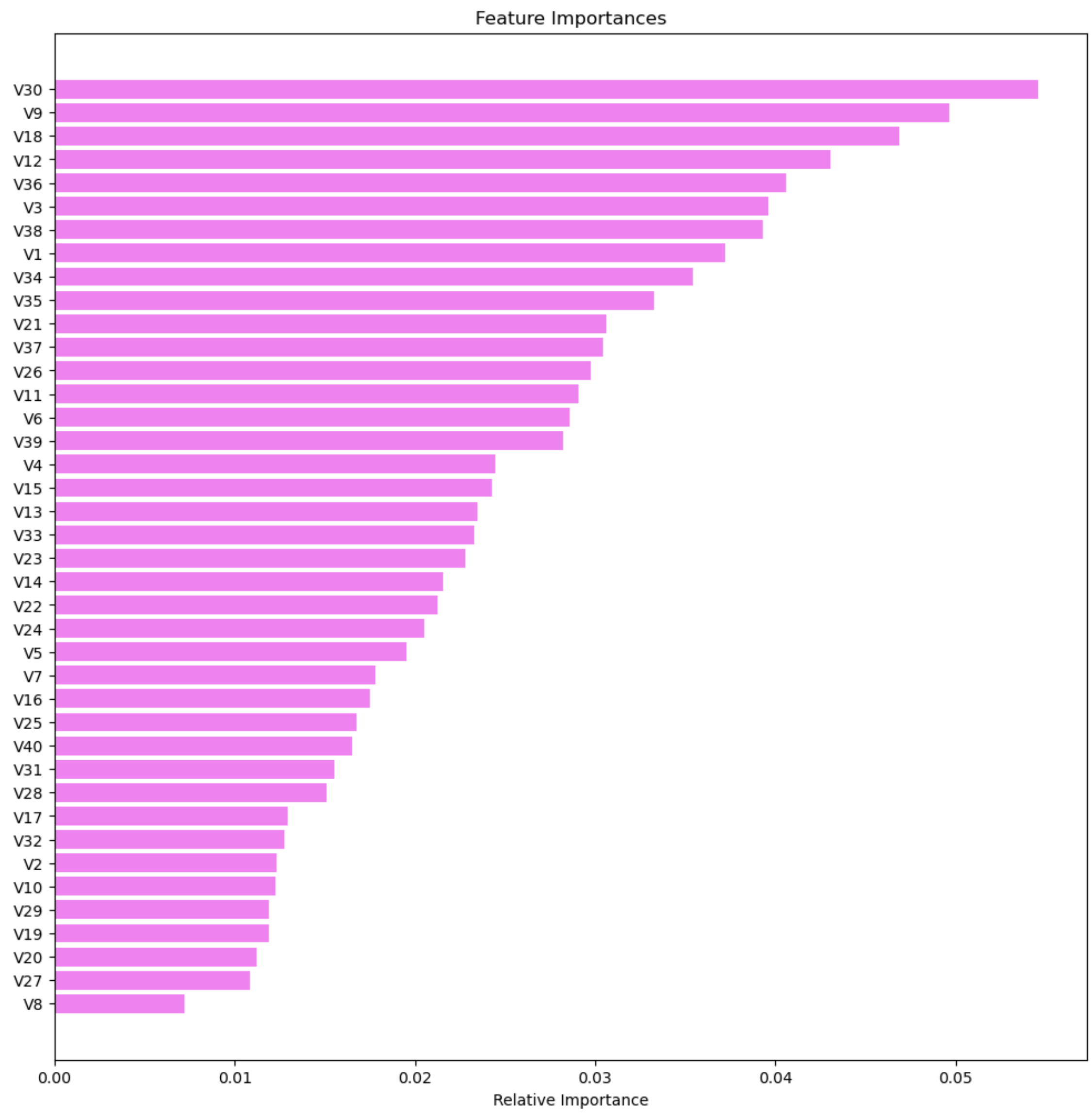
Out[50]:

	Gradient Boosting	Random Forest	Ada
Accuracy	0.971	0.935	0.979
Recall	0.878	0.881	0.849
Precision	0.683	0.457	0.789
F1	0.769	0.602	0.818

My best preforming model was Ada so thats what I'll use to build my final model

In [51]:
```
feature_names = X_train.columns
importances = tune_ada.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize=(12, 12))
plt.title("Feature Importances")
plt.barh(range(len(indices)), importances[indices], color="violet", align=
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel("Relative Importance")
plt.show()
```



The 3 most important variables are v30, v9, and v18.

In [54]:
```
# Creating new pipeline with best parameters
Final_pipe = Pipeline(
    steps=[
        ("imputer", SimpleImputer(strategy='median')),
        (
            "Ada",
            AdaBoostClassifier(
               n_estimators= 200, learning_rate= 0.2, base_estimator= Deci
        )
)
    ])
# Fit the model on training data
Final_pipe.fit(X_train, y_train)
```

Out[54]:
```
Pipeline(steps=[('imputer', SimpleImputer(strategy='median')),
                ('Ada',
                 AdaBoostClassifier(base_estimator=DecisionTreeClassifier
(max_depth=3,

random_state=1),
                                    learning_rate=0.2, n_estimators=20
0))])
```

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Next I will prepare my final model

In [60]:
```
X1 = data.drop(["Target"], axis=1)
y1 = data["Target"]
Xt1 = data_test.drop(["Target"], axis=1)
yt1 = data_test["Target"]
```

In [56]:
```
imputer = SimpleImputer(strategy='median')
X1 = imputer.fit_transform(X1)
```

In [57]:
```
SM = SMOTE(sampling_strategy=1, k_neighbors=5, random_state=1)
X_overf, y_overf = sm.fit_resample(X1, y1)
```

In [58]:
```
Final_pipe.fit(X_overf, y_overf)
```

Out[58]:
```
Pipeline(steps=[('imputer', SimpleImputer(strategy='median')),
                ('Ada',
                 AdaBoostClassifier(base_estimator=DecisionTreeClassifier
(max_depth=3,

random_state=1),
                                    learning_rate=0.2, n_estimators=20
0))])
```

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In [59]:
```
Final_pipe_perf = model_performance_classification_sklearn(Final_pipe,X_te
Final_pipe_perf
```

Out[59]:

	Accuracy	Recall	Precision	F1
0	0.978	0.851	0.774	0.811

Ada using oversampling will yeild the best model

This model will better help predict wind turbine failures

v30, v9, and v18 are the most important variables and play a key role in this model