modelling

May 24, 2023

0.1 Tanzania Water Wells Classification Modelling

0.1.1 Importing relevant dependancies

[53]:
```
# importations
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split, GridSearchCV,\
    cross_validate
from sklearn.preprocessing import FunctionTransformer, StandardScaler,␣
 ↪OneHotEncoder, LabelEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

from sklearn.feature_selection import SelectKBest, f_classif

from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier

from sklearn.ensemble import RandomForestClassifier

import xgboost as xgb

from sklearn.metrics import accuracy_score, recall_score, confusion_matrix,␣
 ↪plot_confusion_matrix,\
    classification_report

from functions import drop_artefacts_and_nulls, calculate_age
from functions import cross_val_evaluate
import warnings

warnings.filterwarnings('ignore')
%matplotlib inline

#read training data
```

```python
train_set = pd.read_csv('Data/labelled_train_set.csv')

#train set
train_set.head()
```

[53]:

```
      id  amount_tsh date_recorded        funder  gps_height     installer  \
0  69572      6000.0    2011-03-14         Roman        1390         Roman
1   8776         0.0    2013-03-06       Grumeti        1399       GRUMETI
2  34310        25.0    2013-02-25  Lottery Club         686  World vision
3  67743         0.0    2013-01-28        Unicef         263        UNICEF
4  19728         0.0    2011-07-13   Action In A           0       Artisan

   longitude   latitude              wpt_name  num_private  … water_quality  \
0  34.938093  -9.856322                  none            0  …          soft
1  34.698766  -2.147466              Zahanati            0  …          soft
2  37.460664  -3.821329           Kwa Mahundi            0  …          soft
3  38.486161 -11.155298  Zahanati Ya Nanyumbu            0  …          soft
4  31.130847  -1.825359               Shuleni            0  …          soft

  quality_group      quantity  quantity_group                source  \
0          good        enough          enough                spring
1          good  insufficient    insufficient  rainwater harvesting
2          good        enough          enough                   dam
3          good           dry             dry           machine dbh
4          good      seasonal        seasonal  rainwater harvesting

            source_type source_class              waterpoint_type  \
0                spring  groundwater           communal standpipe
1  rainwater harvesting      surface           communal standpipe
2                   dam      surface  communal standpipe multiple
3              borehole  groundwater  communal standpipe multiple
4  rainwater harvesting      surface           communal standpipe

  waterpoint_type_group  status_group
0    communal standpipe    functional
1    communal standpipe    functional
2    communal standpipe    functional
3    communal standpipe  needs_repair
4    communal standpipe    functional

[5 rows x 41 columns]
```

0.1.2 Preprocessing

[2]:
```
#list column names for categorical and numerical
cat_cols = drop_artefacts_and_nulls(train_set).select_dtypes(include='object').
 ↪columns
num_cols = drop_artefacts_and_nulls(train_set).select_dtypes(include='number').
 ↪columns
print('Categorical:\n', cat_cols)
print('Numerical:\n', num_cols)
```

```
Categorical:
 Index(['date_recorded', 'installer', 'basin', 'subvillage', 'lga', 'ward',
       'scheme_management', 'permit', 'extraction_type_class',
       'management_group', 'quality_group', 'quantity', 'source',
       'waterpoint_type', 'status_group'],
      dtype='object')
Numerical:
 Index(['amount_tsh', 'gps_height', 'longitude', 'latitude', 'region_code',
       'district_code', 'population', 'construction_year'],
      dtype='object')
```

[3]:
```
#column groups
cat_cols = ['installer', 'basin', 'subvillage', 'lga', 'ward',␣
 ↪'scheme_management',
       'permit', 'extraction_type_class', 'management_group', 'quality_group',
       'quantity', 'source', 'waterpoint_type']

num_cols = ['amount_tsh', 'gps_height', 'longitude', 'latitude', 'region_code',
       'district_code', 'population', 'construction_year', 'age']
```

Transformers

[4]:
```
#function transformer for dropping irrelevant features and nulls
feature_selector = FunctionTransformer(drop_artefacts_and_nulls)

#feature engineering to calculate age
age_transformer = FunctionTransformer(calculate_age)

#column transformer to transform target
target_transformer = ColumnTransformer(transformers=[
    ('le', LabelEncoder(), ['status_group']),
])

#categorical transformer
cat_transformer = Pipeline(steps=[
    ('ohe', OneHotEncoder(handle_unknown='ignore'))
])
```

```
#numerical transformer
num_transformer = Pipeline(steps=[
    ('scaler', StandardScaler())
])


#Preprocessor
preprocessor = ColumnTransformer(transformers=[
    ('num', num_transformer, num_cols),
    ('cat', cat_transformer, cat_cols),
    # ('target_trans', target_transformer)
])
```

Cleaning Pipelines

[5]:
```
# cleaning pipeline
feature_cleaner = Pipeline(steps=[
    ('feat_select', feature_selector),
    ('age_trans', age_transformer)
])
```

Cleaning the the whole training set before spliting

[6]:
```
clean_train_set = feature_cleaner.fit_transform(train_set)
clean_train_set.head()
```

[6]:
```
   amount_tsh  gps_height     installer  longitude   latitude  \
0      6000.0        1390         Roman  34.938093  -9.856322
1         0.0        1399       GRUMETI  34.698766  -2.147466
2        25.0         686  World vision  37.460664  -3.821329
3         0.0         263        UNICEF  38.486161 -11.155298
5        20.0           0           DWE  39.172796  -4.765587

                     basin   subvillage  region_code  district_code  \
0               Lake Nyasa     Mnyusi B           11              5
1            Lake Victoria      Nyamara           20              2
2                  Pangani      Majengo           21              4
3  Ruvuma / Southern Coast    Mahakamani           90             63
5                  Pangani  Moa/Mwereme            4              8

         lga  … permit  construction_year extraction_type_class  \
0     Ludewa  …  False               1999               gravity
1  Serengeti  …   True               2010               gravity
2  Simanjiro  …   True               2009               gravity
3   Nanyumbu  …   True               1986           submersible
5     Mkinga  …   True               2009           submersible

  management_group  quality_group      quantity                source  \
```

```
0       user-group           good        enough                spring
1       user-group           good  insufficient  rainwater harvesting
2       user-group           good        enough                   dam
3       user-group           good           dry           machine dbh
5       user-group          salty        enough                 other

               waterpoint_type  status_group age
0           communal standpipe    functional  12
1           communal standpipe    functional   3
2  communal standpipe multiple    functional   4
3  communal standpipe multiple  needs_repair  27
5  communal standpipe multiple    functional   2

[5 rows x 23 columns]
```

[7]:
```
#X and Y
X = clean_train_set.drop('status_group', axis=1)
y = clean_train_set['status_group']
```

[8]:
```
y.value_counts()
```

[8]:
```
functional      27864
needs_repair    23092
Name: status_group, dtype: int64
```

Actual Preprocessing Pipeline

[9]:
```
#train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.25,
 ↪stratify=y, random_state=42)
X_train.head()
```

[9]:
```
       amount_tsh  gps_height        installer  longitude   latitude  \
46491         0.0        1146              DWE  33.212282  -2.129424
29041       500.0        1518            Shipo  35.061051  -8.864005
6098          0.0         103  District Council  39.450761 -10.033486
44610         0.0           0              DWE  33.105349  -2.420292
23657         0.0        1386              DWE  34.582432  -8.900268

                          basin  subvillage  region_code  district_code  \
46491             Lake Victoria      Buhoro           20              4
29041                    Rufiji  Ilengititu           11              4
6098   Ruvuma / Southern Coast       Milola           80             23
44610             Lake Victoria    Kiloleli           19              2
23657                    Rufiji     Lulanga           11              4

               lga  … scheme_management  permit construction_year  \
```

```
46491        Bunda  ...              WUG  False            1999
29041       Njombe  ...              VWC  False            2008
6098   Lindi Rural  ...              VWC  False            2004
44610         Magu  ...              VWC   True               0
23657       Njombe  ...              WUA   True            1978

      extraction_type_class  management_group quality_group      quantity  \
46491                 other        user-group         salty           dry
29041             rope pump        user-group          good        enough
6098                gravity        user-group          good        enough
44610              handpump        user-group          good  insufficient
23657               gravity        user-group          good        enough

             source     waterpoint_type   age
46491  shallow well               other    14
29041      hand dtw           hand pump     3
6098          river  communal standpipe     9
44610  shallow well           hand pump  2011
23657         river  communal standpipe    33

[5 rows x 22 columns]
```

[10]:
```python
#fit cleaned data into pipeline
# clean_X_train = feature_cleaner.fit_transform(X_train).drop('status_group',␣
↪axis=1)
# clean_X_train.head()
```

[11]:
```python
# reassign column groups
cat_cols = clean_train_set.select_dtypes(include='object').columns
num_cols = clean_train_set.select_dtypes(include='number').columns
print('Categorical:\n', cat_cols)
print('Numerical:\n', num_cols)
```

```
Categorical:
 Index(['installer', 'basin', 'subvillage', 'lga', 'ward', 'scheme_management',
       'permit', 'extraction_type_class', 'management_group', 'quality_group',
       'quantity', 'source', 'waterpoint_type', 'status_group'],
      dtype='object')
Numerical:
 Index(['amount_tsh', 'gps_height', 'longitude', 'latitude', 'region_code',
       'district_code', 'population', 'construction_year', 'age'],
      dtype='object')
```

[33]:
```python
#compare target and X lengt
print('Target length:',len(y_train))
print('Predictor length:', len(X_train))
```

```
Target length: 38217
Predictor length: 38217
```

[13]:
```
#label encode target
le = LabelEncoder()
y_train = le.fit_transform(y_train)
y_train = y_train.reshape([-1,1])
y_train
```

[13]:
```
array([[1],
       [0],
       [0],
       …,
       [1],
       [0],
       [0]])
```

0.1.3 Modelling and Evaluation

The models to be built and evaluated are: 1. `logistic regression` (baseline) 2. `decision tree classifier` 3. `random forest classifier` 4. `knn classifier`

> Since the problem has been manipulated into a binary classification, **Logistic Regression** will be used as the baseline. It is a suitable model for binary problems.

Modelling Pipelines

Logistic Regression

[14]:
```
#Logistic Regression Pipeline
logreg_pipe0 = Pipeline(steps=[
    ('prep', preprocessor),
    ('logreg', LogisticRegression(class_weight='balanced'))
])
```

[15]:
```
logreg_pipe0.fit(X_train, y_train)
```

[15]:
```
Pipeline(steps=[('prep',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('scaler',
StandardScaler())]),
                                                  ['amount_tsh', 'gps_height',
                                                   'longitude', 'latitude',
                                                   'region_code',
                                                   'district_code',
                                                   'population',
                                                   'construction_year',
                                                   'age']),
                                                 ('cat',
```

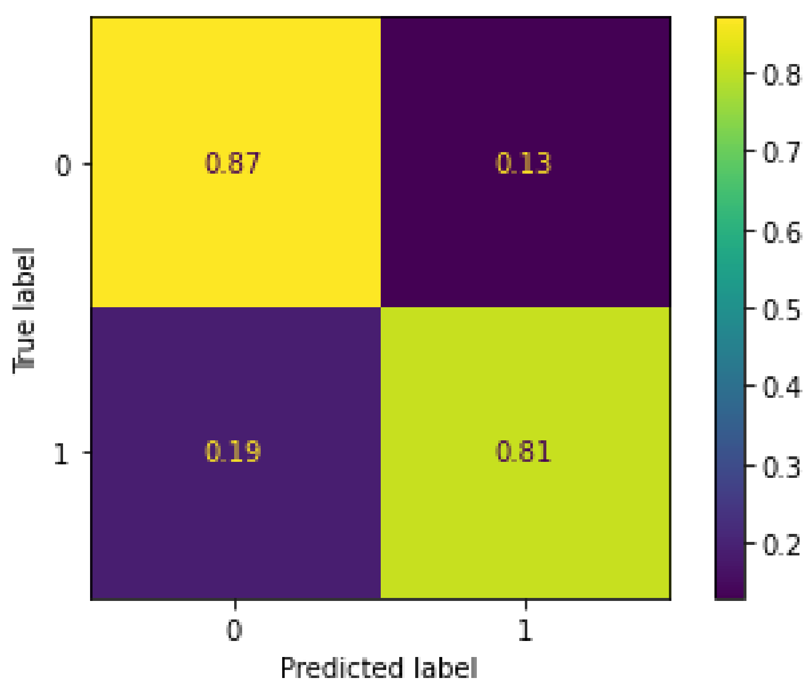
```
                                                    Pipeline(steps=[('ohe',
OneHotEncoder(handle_unknown='ignore'))]),
                                                    ['installer', 'basin',
                                                     'subvillage', 'lga', 'ward',
                                                     'scheme_management',
                                                     'permit',
                                                     'extraction_type_class',
                                                     'management_group',
                                                     'quality_group', 'quantity',
                                                     'source',
                                                     'waterpoint_type'])])),
                ('logreg', LogisticRegression(class_weight='balanced'))])
```

[16]:
```
cross_val_evaluate(logreg_pipe0, X_train, y_train)
```

```
[0.85640925 0.85261505 0.84974161 0.85546543 0.85255446]
Train Accuracy 0.8533571598371328


[0.78663004 0.78388278 0.7960225  0.79196651 0.7804527 ]
Cross-Validation Accuracy 0.7877909063765403


Training Recall: 0.8218286204945148
Test Recall: 0.7436916589028589
```



Decision Tree

[17]:
```
#Decision Tree pipeline
d_tree_pipe0 = Pipeline(steps=[
    ('prep', preprocessor),
    ('d_tree0', DecisionTreeClassifier(random_state=42,
                                       max_depth=10,
                                       class_weight='balanced'))
])
```

[18]:
```
#fit d_tree0
d_tree_pipe0.fit(X_train, y_train)
```

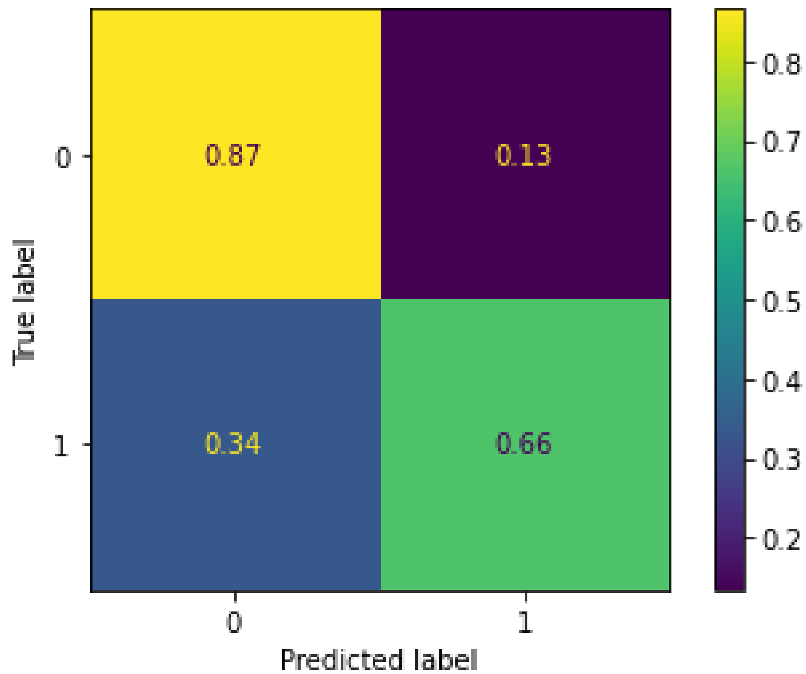
[18]:
```
Pipeline(steps=[('prep',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('scaler',
StandardScaler())]),
                                                  ['amount_tsh', 'gps_height',
                                                   'longitude', 'latitude',
                                                   'region_code',
                                                   'district_code',
                                                   'population',
                                                   'construction_year',
                                                   'age']),
                                                 ('cat',
                                                  Pipeline(steps=[('ohe',
OneHotEncoder(handle_unknown='ignore'))]),
                                                  ['installer', 'basin',
                                                   'subvillage', 'lga', 'ward',
                                                   'scheme_management',
                                                   'permit',
                                                   'extraction_type_class',
                                                   'management_group',
                                                   'quality_group', 'quantity',
                                                   'source',
                                                   'waterpoint_type'])])),
                ('d_tree0',
                 DecisionTreeClassifier(class_weight='balanced', max_depth=10,
                                        random_state=42))])
```

[19]:
```
#cross validate and evaluate
cross_val_evaluate(d_tree_pipe0, X_train, y_train)
```

```
[0.77928237 0.77470317 0.78007457 0.77961667 0.76692615]
Train Accuracy 0.7761205860243526


[0.75837258 0.75130822 0.76409787 0.75886432 0.74604213]
Cross-Validation Accuracy 0.7557370226142772
```

```
Training Recall: 0.7027971149142014
Test Recall: 0.67989064868531
```



Random Forest Classifier

[20]:
```
#Random Forest Pipeline
rf_pipe0 = Pipeline(steps=[
    ('prep', preprocessor),
    ('rf0', RandomForestClassifier(max_depth=5,
                                   n_estimators=50,
                                   class_weight='balanced',
                                   random_state=42))
])
```

[21]:
```
#fit random forest 0
rf_pipe0.fit(X_train, y_train)
```

[21]:
```
Pipeline(steps=[('prep',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('scaler',
StandardScaler())]),
                                                  ['amount_tsh', 'gps_height',
                                                   'longitude', 'latitude',
```

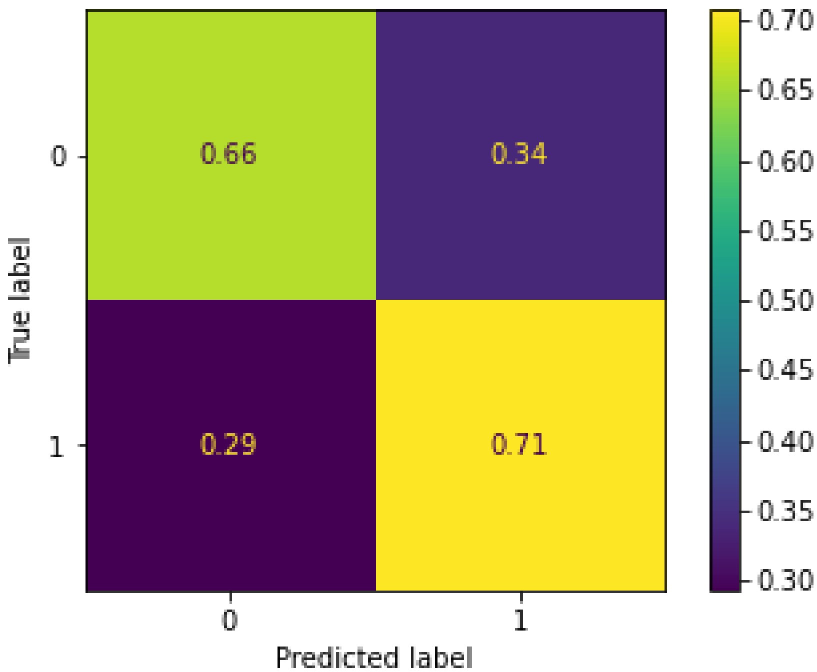
```
                                                         'region_code',
                                                         'district_code',
                                                         'population',
                                                         'construction_year',
                                                         'age']),
                                                       ('cat',
                                                        Pipeline(steps=[('ohe',
OneHotEncoder(handle_unknown='ignore'))]),
                                                        ['installer', 'basin',
                                                         'subvillage', 'lga', 'ward',
                                                         'scheme_management',
                                                         'permit',
                                                         'extraction_type_class',
                                                         'management_group',
                                                         'quality_group', 'quantity',
                                                         'source',
                                                         'waterpoint_type'])])),
                ('rf0',
                 RandomForestClassifier(class_weight='balanced', max_depth=5,
                                        n_estimators=50, random_state=42))])
```

[22]:
```python
#cross validate / evaluate
cross_val_evaluate(rf_pipe0, X_train, y_train)
```

```
[0.70061819 0.7033003  0.69238569 0.67698044 0.69693203]
Train Accuracy 0.6940433304015843


[0.68524333 0.70185767 0.69750098 0.66766976 0.69187492]
Cross-Validation Accuracy 0.688829331388349


Training Recall: 0.7002138008889498
Test Recall: 0.6928224236551496
```



KNN Model

[23]:
```
#KNN pipeline
knn_pipe0 = Pipeline(steps=[
    ('prep', preprocessor),
    ('knn_pipe0', KNeighborsClassifier())
])
#fit knn
knn_pipe0.fit(X_train, y_train)
```

[23]:
```
Pipeline(steps=[('prep',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('scaler',
StandardScaler())]),
                                                  ['amount_tsh', 'gps_height',
                                                   'longitude', 'latitude',
                                                   'region_code',
                                                   'district_code',
                                                   'population',
                                                   'construction_year',
                                                   'age']),
                                                 ('cat',
                                                  Pipeline(steps=[('ohe',
OneHotEncoder(handle_unknown='ignore'))]),
                                                  ['installer', 'basin',
```

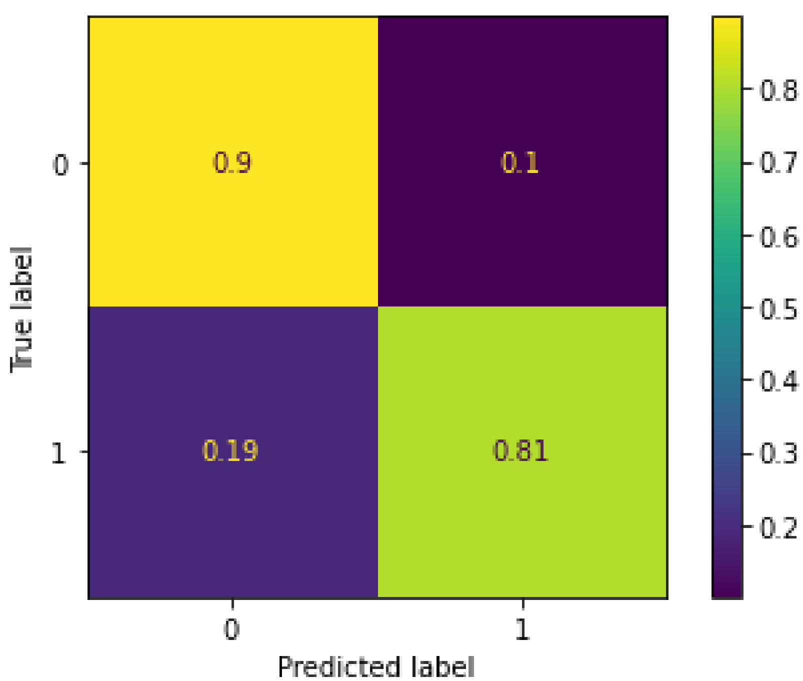
```
                                                 'subvillage', 'lga', 'ward',
                                                 'scheme_management',
                                                 'permit',
                                                 'extraction_type_class',
                                                 'management_group',
                                                 'quality_group', 'quantity',
                                                 'source',
                                                 'waterpoint_type'])])),
                ('knn_pipe0', KNeighborsClassifier())])
```

[24]:
```
#evaluate KNN
cross_val_evaluate(knn_pipe0, X_train, y_train)
```

```
[0.85274589 0.85366173 0.85337215 0.85206385 0.85494211]
Train Accuracy 0.8533571427200535


[0.78584511 0.78506018 0.78660212 0.79013476 0.78660212]
Cross-Validation Accuracy 0.7868488576400579


Training Recall: 0.8013308751645006
Test Recall: 0.7250421479727291
```



*The KNN model has a longer runtime than the other models for little improvement in performance. No thank you!

And ofcourse, we have to have the XGBoost. YOU SIMPLY MUST (X D)

Extreme Gradient Boost

[54]:
```
# XGBoost Pipeline
xgb_pipe = Pipeline(steps=[
    ('prep', preprocessor),
    ('xgb_0', xgb.XGBClassifier(learning_rate=0.1,
            max_depth=3,
            min_child_weight=1,
            gamma=0,
            subsample=0.8,
            colsample_bytree=0.8,
            objective='binary:logistic',
            n_estimators=100,
            seed=42))
])
```

[55]:
```
# fit XGBoost classifer
xgb_pipe.fit(X_train, y_train)
```

[55]:
```
Pipeline(steps=[('prep',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('scaler',
StandardScaler())]),
                                                  ['amount_tsh', 'gps_height',
                                                   'longitude', 'latitude',
                                                   'region_code',
                                                   'district_code',
                                                   'population',
                                                   'construction_year',
                                                   'age']),
                                                 ('cat',
                                                  Pipeline(steps=[('ohe',
OneHotEncoder(handle_unknown='ignore'))]),
                                                  ['installer', 'basin',
                                                   'subvillage', 'lga', 'ward',
                                                   '…
                               colsample_bytree=0.8, gamma=0, gpu_id=-1,
                               importance_type='gain',
                               interaction_constraints='', learning_rate=0.1,
                               max_delta_step=0, max_depth=3,
                               min_child_weight=1, missing=nan,
                               monotone_constraints='()', n_estimators=100,
                               n_jobs=0, num_parallel_tree=1, random_state=42,
                               reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
                               seed=42, subsample=0.8, tree_method='exact',
```

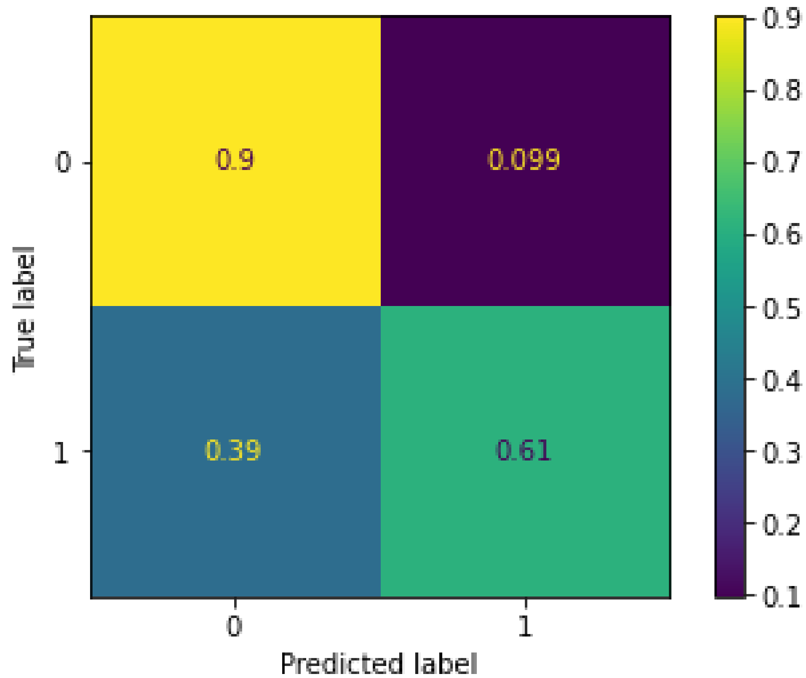
```
validate_parameters=1, verbosity=None))])
```

[56]:
```
#Evaluate
cross_val_evaluate(xgb_pipe, X_train, y_train)
```

```
[0.77035293 0.77051647 0.77186498 0.77225747 0.77052397]
Train Accuracy 0.7711031652344775


[0.76569859 0.76439037 0.76815387 0.77024729 0.75768677]
Cross-Validation Accuracy 0.7652353764501202


Training Recall: 0.6067036916496574
Test Recall: 0.5995716512201905
```



Event the 'ol reliable XGBoost preforms worse than the baseline logistic regression model.

Hyperparameter Tuning Logistic Regression model

[25]:
```
# classification_report(y_test, y_pred)
y_true = le.transform(y_test)
y_pred = logreg_pipe0.predict(X_test)
report = classification_report(y_pred=y_pred, y_true=y_true)
```

```
# Print table
print(report)
```

```
              precision    recall  f1-score   support

           0       0.80      0.83      0.81      6966
           1       0.78      0.75      0.77      5773

    accuracy                           0.79     12739
   macro avg       0.79      0.79      0.79     12739
weighted avg       0.79      0.79      0.79     12739
```

[26]:
```
#parameter grid
params = {
    'logreg__penalty': ['l1', 'l2', 'elasticnet'],
    'logreg__C': [0.01, 0.1, 1, 10],
    'logreg__solver': ['newton-cg', 'lbfgs']}
#Perform Grid Search
grid_search_lr0 = GridSearchCV(logreg_pipe0, params, cv=5)
grid_search_lr0.fit(X_train, y_train)

#Evaluate gridsearch
print(f'Best Hyperparameters: {grid_search_lr0.best_params_}')
print(f'Best Score: {grid_search_lr0.best_score_}')
```

```
Best Hyperparameters: {'logreg__C': 1, 'logreg__penalty': 'l2',
'logreg__solver': 'newton-cg'}
Best Score: 0.790826219878948
```

Fit and package Best model

Ideal Model

[27]:
```
#Best pipeline
ideal_pipe = Pipeline(steps=[
    ('prep', preprocessor),
    ('log_reg_best', LogisticRegression(penalty='l2',
                                        C=1,
                                        solver='newton-cg' ))
])
```

[28]:
```
#fit ideal pipeline
ideal_pipe.fit(X_train, y_train)
```

[28]:
```
Pipeline(steps=[('prep',
                 ColumnTransformer(transformers=[('num',
```

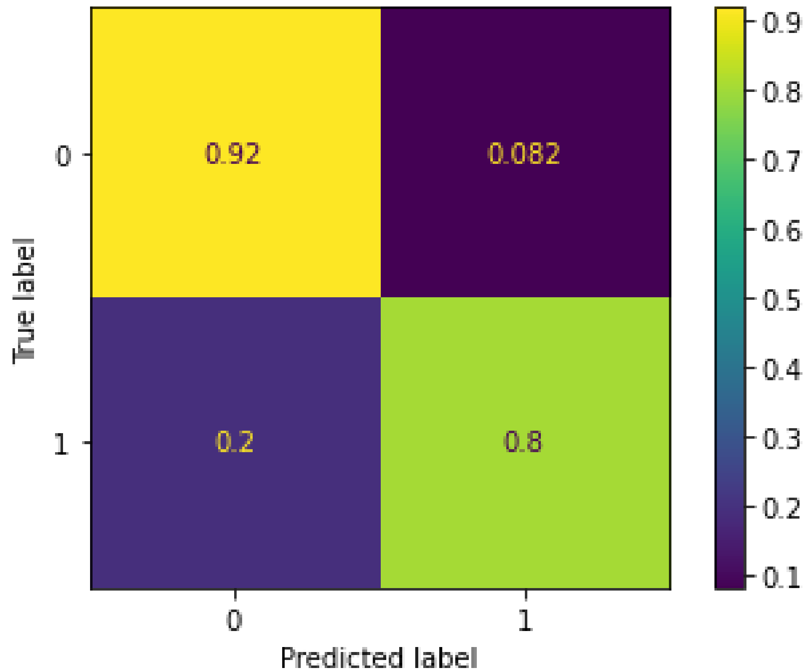
```
                                                  Pipeline(steps=[('scaler',
StandardScaler())]),
                                                   ['amount_tsh', 'gps_height',
                                                    'longitude', 'latitude',
                                                    'region_code',
                                                    'district_code',
                                                    'population',
                                                    'construction_year',
                                                    'age']),
                                                  ('cat',
                                                   Pipeline(steps=[('ohe',
OneHotEncoder(handle_unknown='ignore'))]),
                                                   ['installer', 'basin',
                                                    'subvillage', 'lga', 'ward',
                                                    'scheme_management',
                                                    'permit',
                                                    'extraction_type_class',
                                                    'management_group',
                                                    'quality_group', 'quantity',
                                                    'source',
                                                    'waterpoint_type'])])),
                ('log_reg_best', LogisticRegression(C=1, solver='newton-cg'))])
```

[30]:
```
# cross val evaluation
cross_val_evaluate(ideal_pipe, X_train, y_train)
```

```
[0.87017957 0.87073562 0.86835219 0.87018382 0.8701184 ]
Train Accuracy 0.8699139197696514


[0.79173208 0.79029304 0.80321863 0.7960225  0.78437786]
Cross-Validation Accuracy 0.7931288231030292


Training Recall: 0.808793825525506
Test Recall: 0.7180544375746509
```



Try Feature Selection > * Use Seleck K-Best using *chi_square* test

[50]:
```
#Model with feature selector
ideal_pipe1 = Pipeline(steps=[
    ('prep', preprocessor),
    ('feat_select', SelectKBest(score_func=f_classif)),
    ('log_reg_2', LogisticRegression())
])
# ideal_pipe1.fit(X_train, y_train)
```

[52]:
```
#Tune Hyperparameters
params = {
    'feat_select__k': [5, 10, 15],
    'log_reg_2__penalty': ['l2'],
    'log_reg_2__C': [0.01, 0.1, 1,],
    'log_reg_2__solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag']
}

# Perform grid search cross-validation to find the best hyperparameters
ideal_pipe1_grdsrch = GridSearchCV(ideal_pipe1, params, cv=5)

# Fit the grid search to the training data
ideal_pipe1_grdsrch.fit(X_train, y_train)

# Print the best hyperparameters and their corresponding score
```

```python
print("Best hyperparameters: ", ideal_pipe1_grdsrch.best_params_)
print("Best score: ", ideal_pipe1_grdsrch.best_score_)
```

```
Best hyperparameters:  {'feat_select__k': 10, 'log_reg_2__C': 0.1,
'log_reg_2__penalty': 'l2', 'log_reg_2__solver': 'liblinear'}
Best score:  0.7244681161346271
```

Using a `sklearn`'s `SelectKBest` feature selector worsens our overall model score. This probably ar a result of the increased bias.

0.1.4 Conclusion

- The Baseline **Logistic Regression** performs well on our classification metrics i.e **accuracy** and **recall** Accuracy is a valid metric as the class imbalance is negligible as seen in the data exploration
- The **KNN model** performs similarly to the Logistic Regression. However, due to its exponentially increasing time complexity, this model has a much longer runtime The *runtime* does not justify using this model.
- Both **Decision Trees** and their ensemble counterpart, **Random Forest** performed worse than the baseline model.
- After tuning the Logistic Regression model, as it preforms best, we obtain the best parameters.
- Using a feature selector proved detrimental to the modelling process.

  `BEST MODEL`: **logistic regression(tuned)**