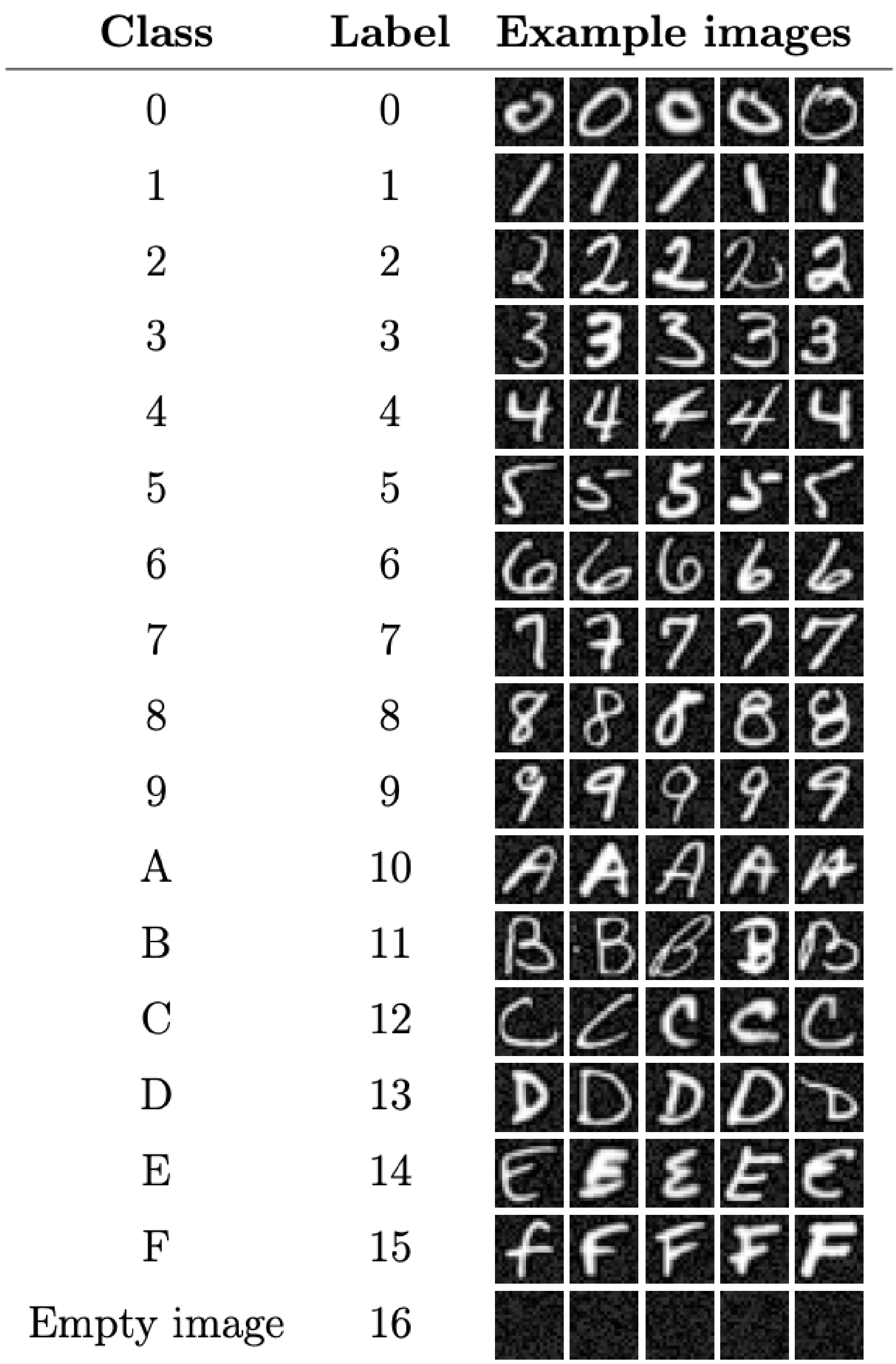
In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import normalize
from sklearn.preprocessing import MinMaxScaler, StandardScaler, MaxAbsScale
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score,
from sklearn.svm import LinearSVC
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
import plotly.express as px
from sklearn.pipeline import Pipeline
from sklearn.base import BaseEstimator, TransformerMixin
import plotly.graph_objects as go
from tabulate import tabulate
from joblib import dump, load
from sklearn.svm import SVC
from imblearn.over_sampling import RandomOverSampler
from imblearn.pipeline import Pipeline as imbPipeline



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

The dataset

In [ ]:
```
X = np.load('data/emnist_hex_images.npy')
y = np.load('data/emnist_hex_labels.npy')
```

DATA EXPLORATION

Below we can see the dataset and how and some few examples from each of them.



Class	Label	Example images
0	0	
1	1	
2	2	
3	3	
4	4	
5	5	
6	6	
7	7	
8	8	
9	9	
A	10	
B	11	
C	12	
D	13	
E	14	
F	15	
Empty image	16	

class_distribution(y):

uses plotly.express bar method to visualize how many images are in each label

In [ ]:
```
data = pd.Series(y).value_counts().sort_index()
fig = px.bar(data, labels= {'value': 'total in dataset', 'index': 'digit'},
fig.update_xaxes(tickvals= list(range(0, 17)))
fig.show()
```

This cell uses plotly express and pandas to visualize the frequency of different pixel values in the images. This was done to see how many gray pixels there are in the dataset, so we could consider modifying them. First we converted the numpy array to a pandas dataframe. Then we could create a column for each pixel value, 1 to 400 and then use numpy bincount to count the occurences of the different values. And at last, create a easy to understand plot.

In [ ]:
```
XX = pd.DataFrame(X, columns = [str(i) for i in range(400)])
value_counts = np.bincount(XX.values.flatten())

df_plot = pd.DataFrame({'Pixel Value': range(len(value_counts)), 'Frequency

color1 = px.colors.qualitative.Dark2[7]
color2 = px.colors.qualitative.Dark2[6]
color3 = px.colors.qualitative.Dark2[5]
color_map = {
    'Pixel Value < 100': color1,
    'Pixel Value between 100 and 254': color2,
    'Pixel Value > 254': color3
}
color_categories = pd.cut(df_plot['Pixel Value'],
                           bins=[-np.inf, 100, 254, np.inf],
                           labels=['Pixel Value < 100', 'Pixel Value betweer
                           include_lowest=True)

fig = px.bar(df_plot, x='Pixel Value', y='Frequency',
            title='Frequency of Pixel Values in the Dataset',
            labels={'Pixel Value': 'Pixel Value (0-255)', 'Frequency': 'Frec
            log_y = True,
            color=color_categories,
            color_discrete_map=color_map)
fig.update_layout(height=600)

fig.show()
```

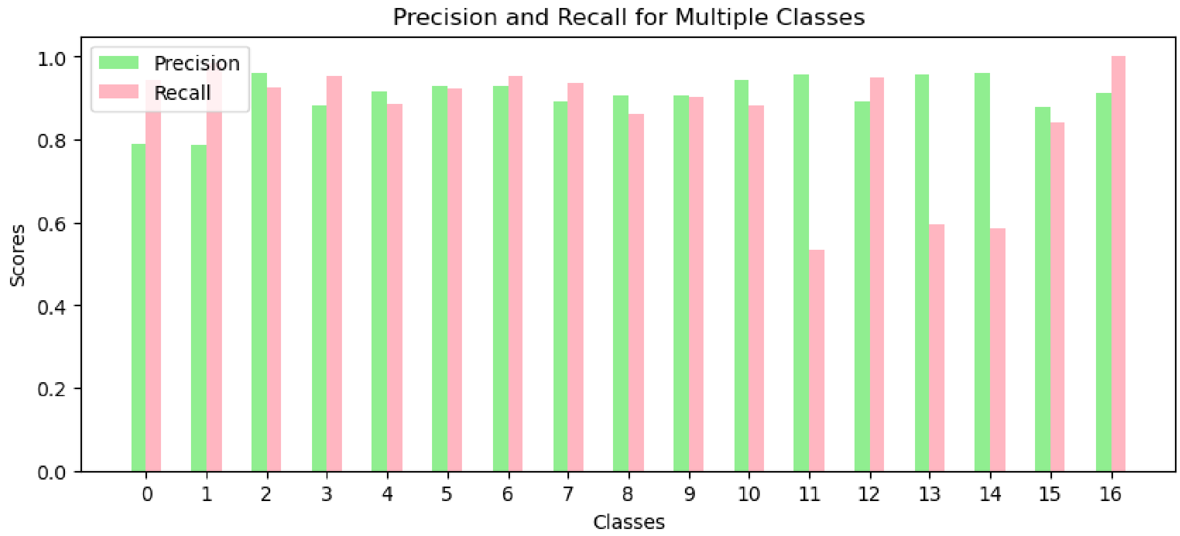
Split the data into 80% train data, 10% validation data and 10% train data. Define random_state for reproducibility

In [ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
X_test, X_val, y_test, y_val = train_test_split(X_test, y_test, test_size =
```

label_errors(y_test, y_pred): A function for visualizing the presicion and recall values for each class

In [ ]:
```
def label_errors(y_test, y_pred):
    classes = list(range(0, 17))
    presicion = [precision_score(y_test, y_pred, labels= [n], average= 'mic
    recall = [recall_score(y_test, y_pred, labels= [n], average= 'micro') fc
    fig, ax = plt.subplots(figsize=(10, 4))


    bar_width = 0.25

    x = range(len(classes))

    #bar plots for precision and recall
    precision_bars = ax.bar(x, presicion, width=bar_width, label='Precision
    recall_bars = ax.bar([i + bar_width for i in x], recall, width=bar_widtl

    ax.set_xticks([i + bar_width/2 for i in x])
    ax.set_xticklabels(classes)

    ax.set_xlabel('Classes')
```

```
    ax.set_ylabel('Scores')
    ax.set_title('Precision and Recall for Multiple Classes')
    ax.legend(loc='best')

    plt.show()

model = KNeighborsClassifier()

model.fit(X_train[-10000:], y_train[-10000:])
y_pred = model.predict(X_train[:10000])

label_errors(y_train[:10000], y_pred)
```



pred_distrb(y_test, y_pred):

a function which plots a confusion matrix for input target values and predicted values.

error_distrb(y_test, y_pred): a function which plots a bar diagram to visualize the amount of errors for each label.

In [ ]:

```
def pred_distrb(y_test, y_pred, min= 0, max= 17):
    matrix = confusion_matrix(y_test, y_pred)
    matrix = matrix.astype(int)

    layout = {
        "title": "Prediction distribution",
        "xaxis": {"title": "Predicted digit"},
        "yaxis": {"title": "Real digit"}
    }

    fig = go.Figure(data=go.Heatmap(z=matrix,
                                    x= list(range(0, 17)),
                                    y= list(range(min, max)),
                                    hoverongaps=False,
                                    colorscale = 'gnbu',
                                    colorbar = dict(title = 'Count'),
                                    text = matrix,
                                    showscale = True),
                    layout=layout)
    fig.update_xaxes(tickvals= list(range(0, 17)))
    fig.show()

def error_distrb(y_test, y_pred):
    wrong = y_test[np.argwhere(y_pred != y_test).flatten()]
    data = pd.Series(wrong).value_counts().sort_index()
```

```
    fig = px.bar(data, labels= {'value': 'number of erros', 'index': 'digit
    fig.update_xaxes(tickvals= list(range(0, 17)))
    fig.show()
```

In [ ]:
```
pred_distrb(y_train[:10000], y_pred)
error_distrb(y_train[:10000], y_pred)
```

Defining the DigitClassifier Class

denoise(image): a function to denoise an image. It changes all pixel values under 100 to 0, and pixel values 254 to 255.

In [ ]:
```
def denoise(image):
    mask_255 = image >= 254
    mask_0 = (image < 100)

    image[mask_255] = 255
    image[mask_0] = 0


    return image
```

A class we needed to create in order to implement the denoise function inside the pipeline.

In [ ]:
```
class Denoise(BaseEstimator, TransformerMixin):
    def __init__(self):
        pass

    def fit(self, X, y=None):
        return self


    def transform(self, X):
        # Apply denoise function to each image in X
        for i in range(len(X)):
            X[i] = denoise(X[i])
        return X
```

Our DigitClassifier class for hyperparameter-tuning and cross-validation. Is initialized with the input of a classifier model, a scaler and chosen hyperparameters for the model.

grid_search_pipe(self, X_train, y_train, pipeline= None): performs a grid search of the pipeline, performs the pipeline steps, and cross validates with the hyperparameters. returns the best model, what score it got, and what parameters it had.

train(self, X_train, y_train): creates the pipeline calls on grid_search pipe prints its results returns the best model

test(self, X_test, y_test): tests the best model from train on the validation data. also prints different performance measures

In [ ]:
```
class DigitClassifier:
```

```
    def __init__(self, model, scaler, params):
        self.model = model
        self.scaler = scaler
        self.params = params
        self.best_model = None
        self.val_score = None
        self.best_params = None

    def grid_search_pipe(self, X_train, y_train, pipeline=None):

        grid = GridSearchCV(pipeline, self.params, cv=4, n_jobs=-1, verbose=
        grid.fit(X_train, y_train)

        return grid.best_estimator_, grid.best_score_, grid.best_params_

    def train(self, X_train, y_train):

        ros = RandomOverSampler()

        pipeline_steps = [
            ('oversampler', ros),
            ('denoise', Denoise()),
            ('scaler', self.scaler),
            ('model', self.model)
        ]


        pipeline = imbPipeline(pipeline_steps)

        best_model, best_score, best_params = self.grid_search_pipe(X_train,

        denoise_name = type(Denoise()).__name__
        oversampler = type(ros).__name__
        scaler_name = type(self.scaler).__name__
        model_name = type(self.model).__name__
        print(f'Our best model: ({model_name}, oversampler: {oversampler}, 

        if (self.best_model is None) or best_score > self.best_model[1]:
            self.best_model = (best_model, best_score)
            self.best_params = best_params

        return self.best_model


    def test(self, X_test, y_test):
        y_pred = self.best_model[0].predict(X_test)
        self.val_score = accuracy_score(y_test, y_pred)


        scores = {
            'Accuracy': accuracy_score(y_test, y_pred),
            'Precision': precision_score(y_test, y_pred, average='weighted'
            'Recall': recall_score(y_test, y_pred, average='weighted'),
            'F1 Score': f1_score(y_test, y_pred, average='weighted')
        }

        data = [(name, val) for name, val in scores.items()]
        print('Score on val data:')
        print(tabulate(data, headers=['Metric', 'Score'], tablefmt='github'

    def y_pred(self):
        return self.best_model[0].predict(X_test)
```

Our class RunModels for implementing the DigitClassifier class for each classifier we want to use. We create a method for each classifier.

KNN, RFC and SVC_ all call on the DigitClassifier class with train and validation data for hyperparamter-tuning.

run_best_model(self, X_test, y_test): It checks which of the 3 best models from the classifiers performs best on the validation data. The model with the best results is then tested on the test data. It prints the final results.

In [ ]:
```
class RunModels:
    def __init__(self, X_train, y_train, X_val, y_val, models = ['RFC', 'KNN
        self.X_train = X_train
        self.y_train = y_train
        self.X_val = X_val
        self.y_val = y_val
        self.models = models
        self.y_pred = None
        self.best_model = None


    def KNN(self, neighbors = [5, 9, 13, 15], weights = ['uniform', 'distanc
        model = KNeighborsClassifier()
        params = {
            'model__n_neighbors': neighbors,
            'model__weights': weights,
            'model__p' : p
        }
        scalers = StandardScaler()


        knn = DigitClassifier(model, scalers, params)


        knn.train(self.X_train, self.y_train)

        knn.test(self.X_val, self.y_val)
        dump(knn, 'KNN.joblib')


    def RFC(self, estimators = [1000], criterion = ['gini', 'entropy'], max_

        model = RandomForestClassifier(max_depth=None, min_samples_split=2,
        params = {
            'model__n_estimators': estimators,
            'model__criterion': criterion,
            'model__max_features' : max_features
        }
        scalers = StandardScaler()


        rfc = DigitClassifier(model, scalers, params)


        rfc.train(self.X_train, self.y_train)

        rfc.test(self.X_val, self.y_val)
        dump(rfc, 'RFC.joblib')

    def SVC_(self, C = [1, 3], gamma = ['scale', 'auto'], kernel = ['rbf',
        model = SVC(cache_size=1000)
```

```
        params = {
            'model__C': C,
            'model__gamma': gamma,
            'model__kernel': kernel,
        }

        scalers = StandardScaler()

        svc = DigitClassifier(model, scalers, params)

        svc.train(self.X_train, self.y_train)

        svc.test(self.X_val, self.y_val)
        dump(svc, 'SVC.joblib')


    def run_best_model(self, X_test, y_test):
        best_accuracy = 0
        output = []
        for i in self.models:
            data = load(i + '.joblib')
            score = data.val_score
            output.append([i, score])
            if score > best_accuracy:
                best_accuracy = score
                self.best_model = i
                params = data.best_params

        print(tabulate(output, headers=['Model', 'Score'], tablefmt='github
        print()
        print(f'Our best model: {self.best_model}\nHyperparameters: {params}


        y_pred = load(self.best_model + '.joblib').best_model[0].predict(X_t
        self.y_pred = y_pred
        print(f'Our best model´s accuracy on test data: {accuracy_score(y_te

        dump(y_pred, 'best_model.joblib')
```

In [ ]:

```
run_models = RunModels(X_train, y_train, X_val, y_val)
```

In [ ]:

```
run_models.KNN()
```

```
Fitting 4 folds for each of 16 candidates, totalling 64 fits
[CV 1/4] END model__n_neighbors=5, model__p=2, model__weights=uniform;, sco
re=0.861 total time=  40.2s
[CV 2/4] END model__n_neighbors=5, model__p=2, model__weights=uniform;, sco
re=0.856 total time=  40.4s
[CV 4/4] END model__n_neighbors=5, model__p=2, model__weights=uniform;, sco
re=0.855 total time=  40.3s
[CV 3/4] END model__n_neighbors=5, model__p=2, model__weights=uniform;, sco
re=0.860 total time=  40.5s
[CV 1/4] END model__n_neighbors=5, model__p=2, model__weights=distance;, sc
ore=0.866 total time=  39.8s
[CV 2/4] END model__n_neighbors=5, model__p=2, model__weights=distance;, sc
ore=0.863 total time=  39.8s
[CV 3/4] END model__n_neighbors=5, model__p=2, model__weights=distance;, sc
ore=0.865 total time=  39.7s
[CV 4/4] END model__n_neighbors=5, model__p=2, model__weights=distance;, sc
ore=0.859 total time=  39.8s
[CV 4/4] END model__n_neighbors=5, model__p=1, model__weights=distance;, sc
ore=0.907 total time= 9.5min
[CV 3/4] END model__n_neighbors=5, model__p=1, model__weights=uniform;, sco
re=0.909 total time= 9.5min
[CV 3/4] END model__n_neighbors=5, model__p=1, model__weights=distance;, sc
ore=0.913 total time= 9.5min
[CV 2/4] END model__n_neighbors=5, model__p=1, model__weights=distance;, sc
ore=0.910 total time= 9.5min
[CV 4/4] END model__n_neighbors=5, model__p=1, model__weights=uniform;, sco
re=0.906 total time= 9.5min
[CV 2/4] END model__n_neighbors=5, model__p=1, model__weights=uniform;, sco
re=0.907 total time= 9.5min
[CV 1/4] END model__n_neighbors=5, model__p=1, model__weights=distance;, sc
ore=0.910 total time= 9.5min
[CV 1/4] END model__n_neighbors=5, model__p=1, model__weights=uniform;, sco
re=0.909 total time= 9.5min
[CV 1/4] END model__n_neighbors=9, model__p=2, model__weights=uniform;, sco
re=0.859 total time=  40.5s
[CV 2/4] END model__n_neighbors=9, model__p=2, model__weights=uniform;, sco
re=0.855 total time=  40.7s
[CV 3/4] END model__n_neighbors=9, model__p=2, model__weights=uniform;, sco
re=0.856 total time=  57.1s
[CV 4/4] END model__n_neighbors=9, model__p=2, model__weights=uniform;, sco
re=0.855 total time=  59.5s
[CV 1/4] END model__n_neighbors=9, model__p=2, model__weights=distance;, sc
ore=0.864 total time=  57.6s
[CV 2/4] END model__n_neighbors=9, model__p=2, model__weights=distance;, sc
ore=0.861 total time=  56.4s
[CV 1/4] END model__n_neighbors=9, model__p=1, model__weights=uniform;, sco
re=0.905 total time= 9.4min
[CV 4/4] END model__n_neighbors=9, model__p=2, model__weights=distance;, sc
ore=0.857 total time=  51.4s
[CV 3/4] END model__n_neighbors=9, model__p=2, model__weights=distance;, sc
ore=0.862 total time=  53.1s
[CV 2/4] END model__n_neighbors=9, model__p=1, model__weights=uniform;, sco
re=0.904 total time=11.1min
[CV 1/4] END model__n_neighbors=9, model__p=1, model__weights=distance;, sc
ore=0.908 total time= 9.3min
[CV 4/4] END model__n_neighbors=9, model__p=1, model__weights=uniform;, sco
re=0.903 total time= 9.4min
[CV 2/4] END model__n_neighbors=9, model__p=1, model__weights=distance;, sc
ore=0.906 total time= 9.4min
[CV 4/4] END model__n_neighbors=9, model__p=1, model__weights=distance;, sc
ore=0.904 total time= 9.4min
[CV 3/4] END model__n_neighbors=9, model__p=1, model__weights=uniform;, sco
re=0.905 total time= 9.4min
[CV 3/4] END model__n_neighbors=9, model__p=1, model__weights=distance;, sc
```

```
ore=0.909 total time= 9.4min
[CV 1/4] END model__n_neighbors=13, model__p=2, model__weights=uniform;, sc
ore=0.859 total time=  37.3s
[CV 2/4] END model__n_neighbors=13, model__p=2, model__weights=uniform;, sc
ore=0.855 total time=  42.3s
[CV 3/4] END model__n_neighbors=13, model__p=2, model__weights=uniform;, sc
ore=0.855 total time=  41.6s
[CV 4/4] END model__n_neighbors=13, model__p=2, model__weights=uniform;, sc
ore=0.851 total time=  42.3s
[CV 1/4] END model__n_neighbors=13, model__p=2, model__weights=distance;, s
core=0.862 total time=  44.4s
[CV 2/4] END model__n_neighbors=13, model__p=2, model__weights=distance;, s
core=0.858 total time=  44.4s
[CV 3/4] END model__n_neighbors=13, model__p=2, model__weights=distance;, s
core=0.858 total time=  41.1s
[CV 4/4] END model__n_neighbors=13, model__p=2, model__weights=distance;, s
core=0.858 total time=  41.0s
[CV 2/4] END model__n_neighbors=13, model__p=1, model__weights=uniform;, sc
ore=0.899 total time= 9.3min
[CV 4/4] END model__n_neighbors=13, model__p=1, model__weights=uniform;, sc
ore=0.897 total time= 9.3min
[CV 1/4] END model__n_neighbors=13, model__p=1, model__weights=uniform;, sc
ore=0.903 total time=11.2min
[CV 3/4] END model__n_neighbors=13, model__p=1, model__weights=uniform;, sc
ore=0.902 total time=11.1min
[CV 4/4] END model__n_neighbors=13, model__p=1, model__weights=distance;, s
core=0.900 total time= 9.1min
[CV 1/4] END model__n_neighbors=13, model__p=1, model__weights=distance;, s
core=0.903 total time=10.5min
[CV 2/4] END model__n_neighbors=13, model__p=1, model__weights=distance;, s
core=0.901 total time=10.5min
[CV 3/4] END model__n_neighbors=13, model__p=1, model__weights=distance;, s
core=0.905 total time=10.5min
[CV 1/4] END model__n_neighbors=15, model__p=2, model__weights=uniform;, sc
ore=0.856 total time=  45.8s
[CV 2/4] END model__n_neighbors=15, model__p=2, model__weights=uniform;, sc
ore=0.853 total time=  45.6s
[CV 1/4] END model__n_neighbors=15, model__p=1, model__weights=uniform;, sc
ore=0.899 total time= 9.1min
[CV 2/4] END model__n_neighbors=15, model__p=1, model__weights=uniform;, sc
ore=0.898 total time= 9.2min
[CV 3/4] END model__n_neighbors=15, model__p=2, model__weights=uniform;, sc
ore=0.854 total time=  45.2s
[CV 4/4] END model__n_neighbors=15, model__p=2, model__weights=uniform;, sc
ore=0.852 total time=  44.8s
[CV 3/4] END model__n_neighbors=15, model__p=1, model__weights=uniform;, sc
ore=0.900 total time= 9.1min
[CV 1/4] END model__n_neighbors=15, model__p=2, model__weights=distance;, s
core=0.861 total time=  41.8s
[CV 2/4] END model__n_neighbors=15, model__p=2, model__weights=distance;, s
core=0.855 total time=  40.2s
[CV 3/4] END model__n_neighbors=15, model__p=2, model__weights=distance;, s
core=0.860 total time=  40.0s
[CV 4/4] END model__n_neighbors=15, model__p=2, model__weights=distance;, s
core=0.856 total time=  39.7s
[CV 4/4] END model__n_neighbors=15, model__p=1, model__weights=uniform;, sc
ore=0.895 total time= 9.0min
[CV 2/4] END model__n_neighbors=15, model__p=1, model__weights=distance;, s
core=0.899 total time= 8.9min
[CV 1/4] END model__n_neighbors=15, model__p=1, model__weights=distance;, s
core=0.901 total time=10.0min
[CV 3/4] END model__n_neighbors=15, model__p=1, model__weights=distance;, s
core=0.904 total time= 8.4min
[CV 4/4] END model__n_neighbors=15, model__p=1, model__weights=distance;, s
```

```
core=0.898 total time= 8.4min
Our best model: (KNeighborsClassifier, denoise function), and scaler (Stand
ardScaler) )
Best hyperparameters: {'model__n_neighbors': 5, 'model__p': 1, 'model__weig
hts': 'distance'}
CV score: 0.9100659746360565
Score on val data:
| Metric    |    Score |
|-----------|----------|
| Accuracy  | 0.914479 |
| Precision | 0.916808 |
| Recall    | 0.914479 |
| F1 Score  | 0.913436 |
```

run*models.SVC*()

In [ ]:
```
run_models.RFC()
```

```
Fitting 4 folds for each of 6 candidates, totalling 24 fits
[CV 2/4] END model__criterion=gini, model__max_features=log2, model__n_esti
mators=1000;, score=0.941 total time= 2.4min
[CV 1/4] END model__criterion=gini, model__max_features=log2, model__n_esti
mators=1000;, score=0.941 total time= 2.4min
[CV 4/4] END model__criterion=gini, model__max_features=log2, model__n_esti
mators=1000;, score=0.937 total time= 2.4min
[CV 3/4] END model__criterion=gini, model__max_features=log2, model__n_esti
mators=1000;, score=0.938 total time= 2.4min
[CV 2/4] END model__criterion=gini, model__max_features=sqrt, model__n_esti
mators=1000;, score=0.943 total time= 4.9min
[CV 1/4] END model__criterion=gini, model__max_features=sqrt, model__n_esti
mators=1000;, score=0.943 total time= 5.0min
[CV 4/4] END model__criterion=gini, model__max_features=sqrt, model__n_esti
mators=1000;, score=0.940 total time= 5.0min
[CV 3/4] END model__criterion=gini, model__max_features=sqrt, model__n_esti
mators=1000;, score=0.941 total time= 5.0min
[CV 1/4] END model__criterion=entropy, model__max_features=sqrt, model__n_e
stimators=1000;, score=0.942 total time= 5.9min
[CV 2/4] END model__criterion=entropy, model__max_features=sqrt, model__n_e
stimators=1000;, score=0.943 total time= 5.9min
[CV 3/4] END model__criterion=entropy, model__max_features=sqrt, model__n_e
stimators=1000;, score=0.939 total time= 5.8min
[CV 4/4] END model__criterion=entropy, model__max_features=sqrt, model__n_e
stimators=1000;, score=0.940 total time= 5.9min
[CV 1/4] END model__criterion=entropy, model__max_features=log2, model__n_e
stimators=1000;, score=0.940 total time= 2.9min
[CV 2/4] END model__criterion=entropy, model__max_features=log2, model__n_e
stimators=1000;, score=0.940 total time= 3.0min
[CV 3/4] END model__criterion=entropy, model__max_features=log2, model__n_e
stimators=1000;, score=0.937 total time= 2.9min
[CV 4/4] END model__criterion=entropy, model__max_features=log2, model__n_e
stimators=1000;, score=0.937 total time= 2.9min
[CV 2/4] END model__criterion=gini, model__max_features=0.3, model__n_estim
ators=1000;, score=0.942 total time=26.6min
[CV 4/4] END model__criterion=gini, model__max_features=0.3, model__n_estim
ators=1000;, score=0.938 total time=26.6min
[CV 3/4] END model__criterion=gini, model__max_features=0.3, model__n_estim
ators=1000;, score=0.941 total time=26.7min
[CV 1/4] END model__criterion=gini, model__max_features=0.3, model__n_estim
ators=1000;, score=0.942 total time=26.8min
[CV 1/4] END model__criterion=entropy, model__max_features=0.3, model__n_es
timators=1000;, score=0.942 total time=27.4min
[CV 2/4] END model__criterion=entropy, model__max_features=0.3, model__n_es
timators=1000;, score=0.942 total time=27.4min
[CV 3/4] END model__criterion=entropy, model__max_features=0.3, model__n_es
timators=1000;, score=0.939 total time=27.3min
[CV 4/4] END model__criterion=entropy, model__max_features=0.3, model__n_es
timators=1000;, score=0.938 total time=27.3min
Our best model: (RandomForestClassifier, denoise function), and scaler (Sta
ndardScaler) )
Best hyperparameters: {'model__criterion': 'gini', 'model__max_features':
'sqrt', 'model__n_estimators': 1000}
CV score: 0.9417794152268848
Score on val data:
| Metric    |    Score |
|-----------|----------|
| Accuracy  | 0.944718 |
| Precision | 0.945017 |
| Recall    | 0.944718 |
| F1 Score  | 0.944557 |
```

In [ ]:

```
best_model = run_models.run_best_model(X_test, y_test)
best_model
```

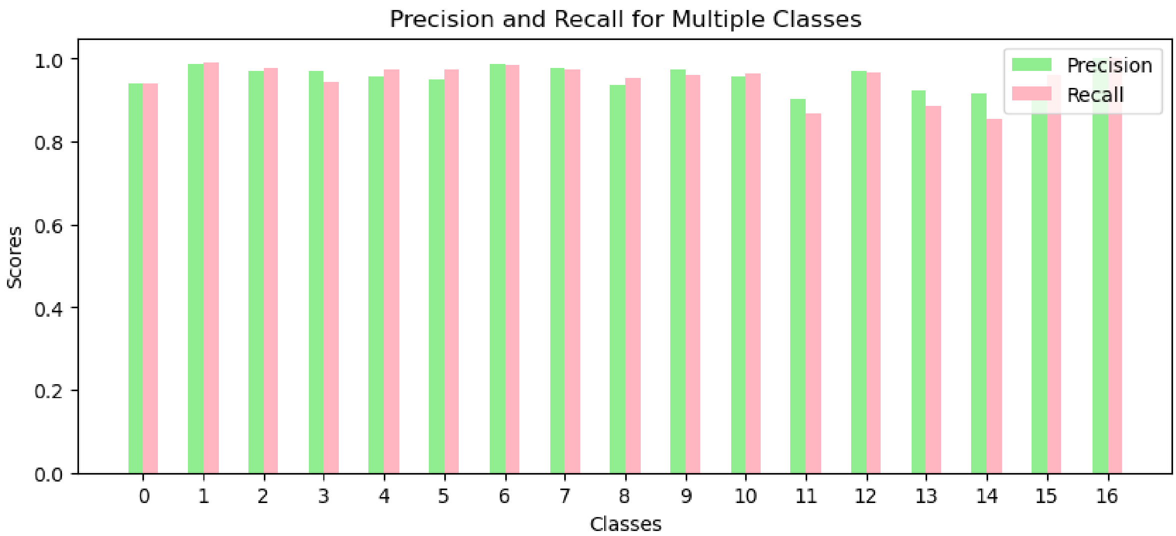
```
| Model    |    Score |
|----------|----------|
| RFC      | 0.944718 |
| KNN      | 0.914479 |
| SVC      | 0.958724 |

Our best model: SVC
Hyperparameters: {'model__C': 3, 'model__gamma': 'auto', 'model__kernel': 'poly'}
Our best model´s accuracy on test data: 0.9603896103896103
```

Plots on our best model

In [ ]:
```
best_y_pred = load('best_model.joblib')
pred_distrb(y_test, best_y_pred)
```

In [ ]:
```
error_distrb(y_test, best_y_pred)
```

In [ ]:
```
label_errors(y_test, best_y_pred)
```

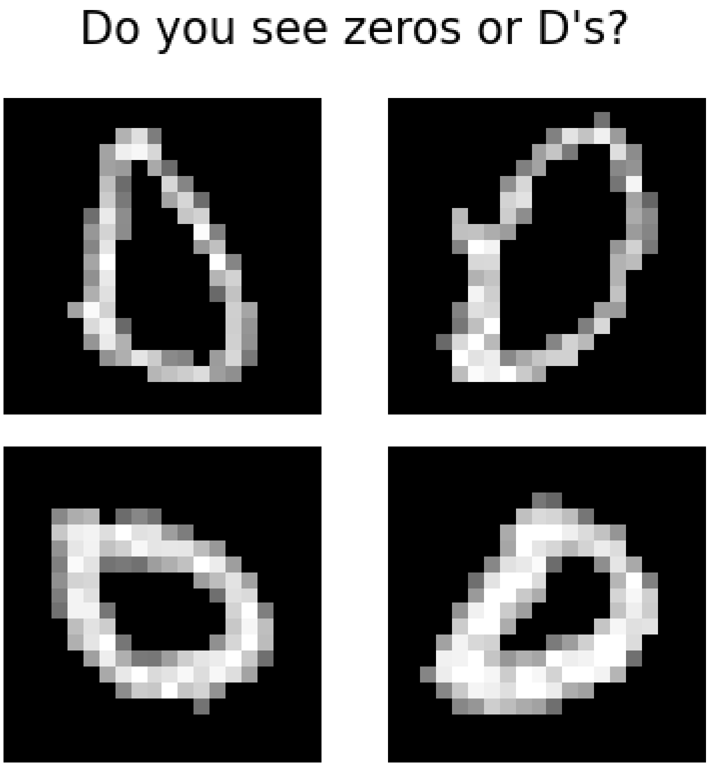


Final thoughts

So what can we learn from this? We have seen that still after oversampling the underrepresented classes, class 11 and 13 (B and D) still get a lot of errors. We have concluded that this is because of the bad data that is in these classes. When random oversampling them, we still reproduce the bad samples from these classes. We will show you some examples below.

In [ ]:
```
l = []
for i in range(1, 5000):
    if y_test[i] == 13 and best_y_pred[i] == 0:
        l.append(X_test[i])

fig, axes = plt.subplots(2, 2, figsize=(4,4))

axes[0,0].imshow(l[0].reshape(20,20), vmin=0, vmax=255, cmap='gray')
axes[0,0].axis('off')

axes[0,1].imshow(l[1].reshape(20,20), vmin=0, vmax=255, cmap='gray')
```

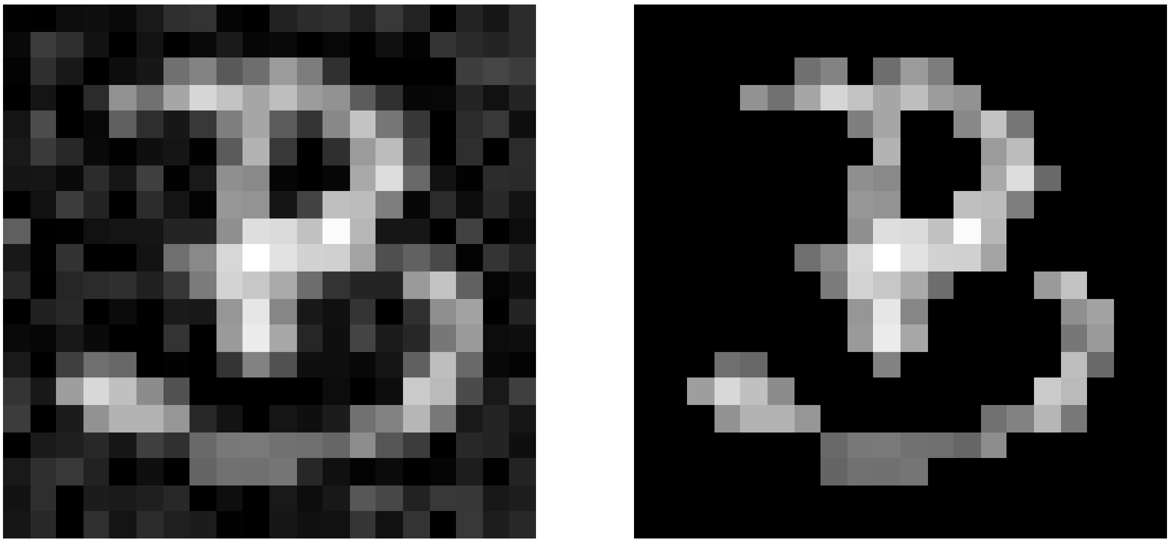
```
axes[0,1].axis('off')

axes[1,0].imshow(l[3].reshape(20,20), vmin=0, vmax=255, cmap='gray')
axes[1,0].axis('off')

axes[1,1].imshow(l[4].reshape(20,20), vmin=0, vmax=255, cmap='gray')
axes[1,1].axis('off')

fig.suptitle("Do you see zeros or D's?", fontsize=16)
plt.tight_layout()
plt.show()
```



In [ ]:

```
fig, axes = plt.subplots(1, 2, figsize=(8,4))


axes[0].imshow(X[10000].reshape(20,20), vmin=0, vmax=255, cmap='gray')
axes[0].axis('off')


axes[1].imshow(denoise(X[10000]).reshape(20,20), vmin=0, vmax=255, cmap='gra
axes[1].axis('off')






fig.suptitle("An image before and after denoising", fontsize=16)
plt.tight_layout()
plt.show()
```

An image before and after denoising



In [ ]: