Machine Learning Project
Task 1

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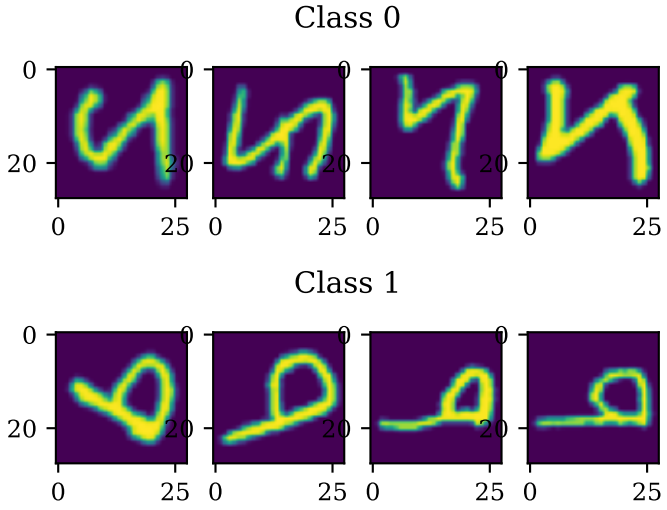
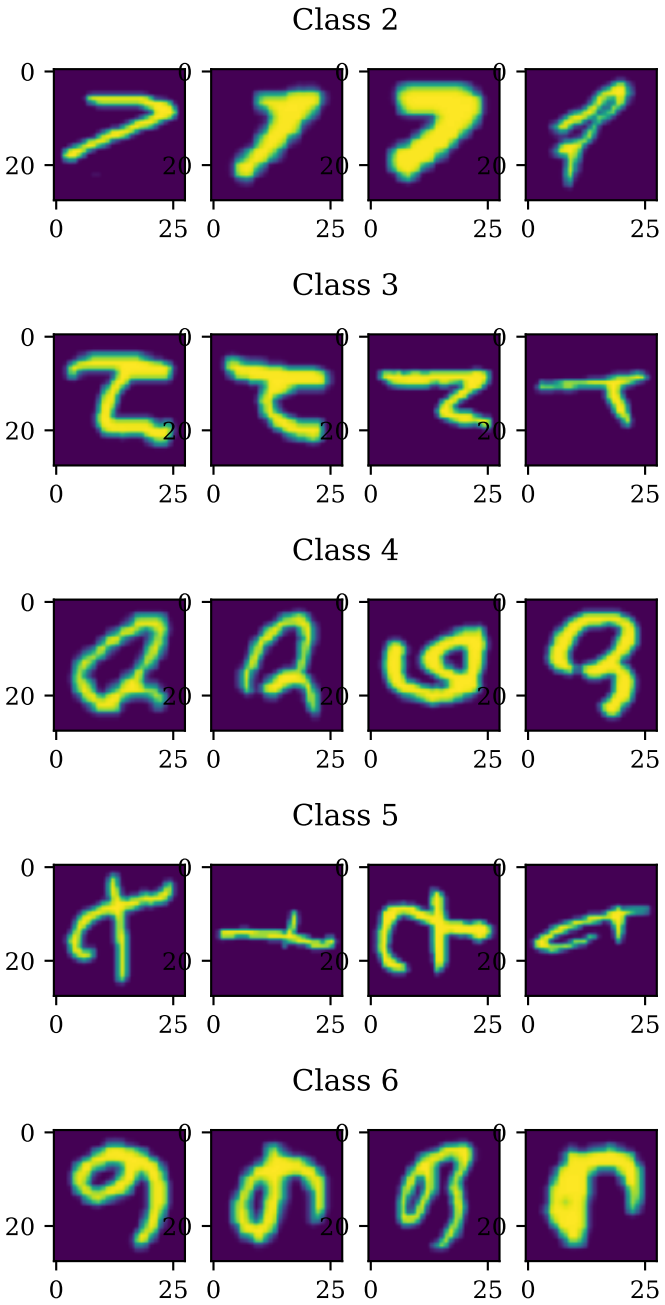
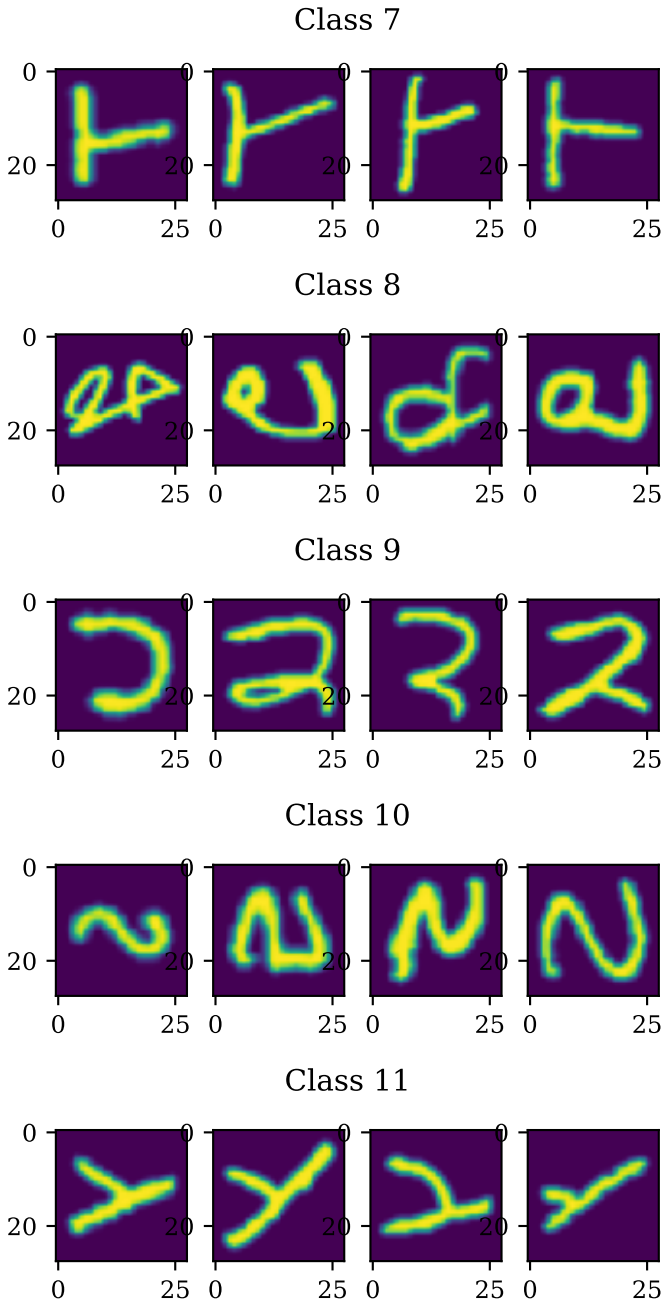
1 K Nearest Neighbor Classification

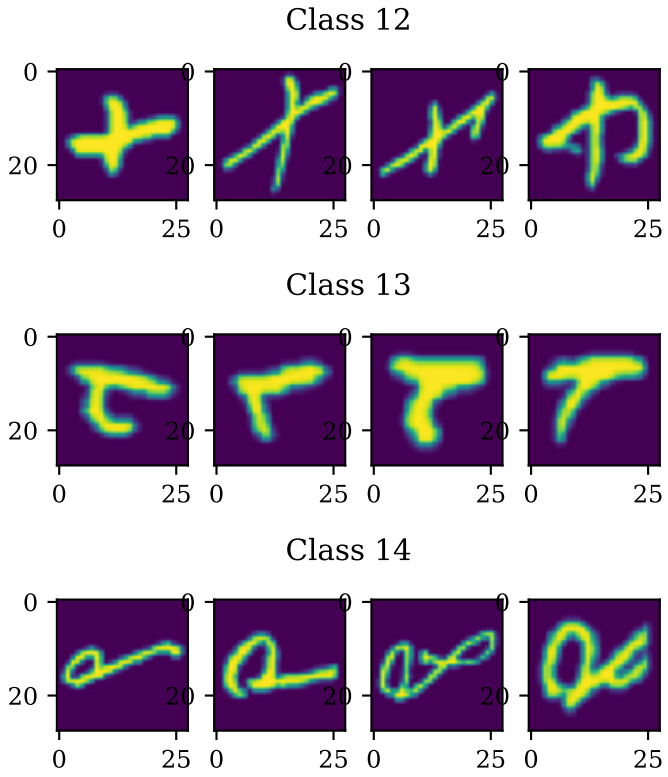
1.1 Classes of the data set

First we look into the data set, which will be used to fit the model as well as evaluate the accuracy of the model. The data consists of a total of 15000 images, each one was assigned with a specific label. Here is what each class in the data set looks like:




Class 2
Class 3
Class 4
Class 5
Class 6
0
20
0
25


Class 7
Class 8
Class 9
Class 10
Class 11
0
20
0
25



There are 15 different classes in the data, which was counted from 0 to 14. Each of these classes may have an unique pattern: For example, Images in class 7 look like a letter 'T', which was rotated 90 degree to the left. Images in class 1 look like a letter 'q', which was rotated 90 degree to the right. It is important to note that through normal observation, it can be very challenging to recognize the pattern or the common properties of all images in the same class. Therefore it is necessary to create a classification, which can be used to determine the class of object that can not be done with simple human observation.

1.2 Implementation of KNN

A class was implemented to define every KNN-classifier. A classifier has many different properties:

- k: The amount of images that we need to identify the label of calculating image
- dist_function: The method to calculate the distance between image

- filter: Filter For the calculating image, which is required later into the task
- return_neighbor: Check if we want to save the k-nearest neighbors for each image, which is useful later to identify neighbors of misclassified images

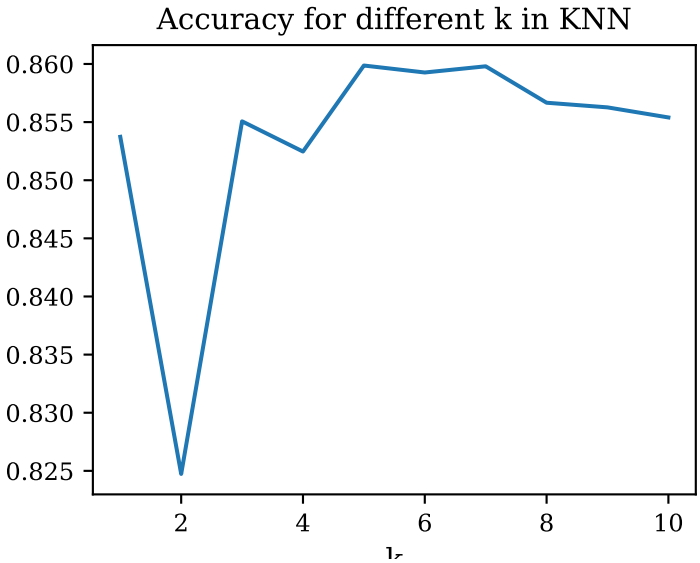
Listing 1: KNN class

```
class KNN:
    def __init__(self, k=5, dist_function=euclidean_distance
            , filter=None, return_neighbor=False):
        self.k = k
        self.dist_function = dist_function
        self.return_neighbor = return_neighbor
        self.filter = filter

    def fit(self, X, y):
        if self.filter is not None:
            X = np.array([convolve(i, self.filter) for i in X])
        self.train_x = X
        self.train_y = y

    def predict(self, X):
        if self.filter is not None:
            X = np.array([convolve(i, self.filter) for i in X])
        return [knn(x, self.train_x, self.k, self.train_y
                , self.dist_function, self.return_neighbor) for x in X]
```

The fit method will get the data as "train data", so we will calculate the distance between the images, which we need to predict the label, with these "train-images". The method predict will call the function knn, which calculate the label for each image in the set. The algorithm of this function was demonstrated in the task sheet and the implementation can be found in knn.py

1.3 m-fold cross validation on different k

We implemented m-fold cross validation and the Euclidean distance functions as described in the task sheet. As the sheet required, we run 5 fold cross validation on the entire set of 15000 images with k vary from 1 to 10.



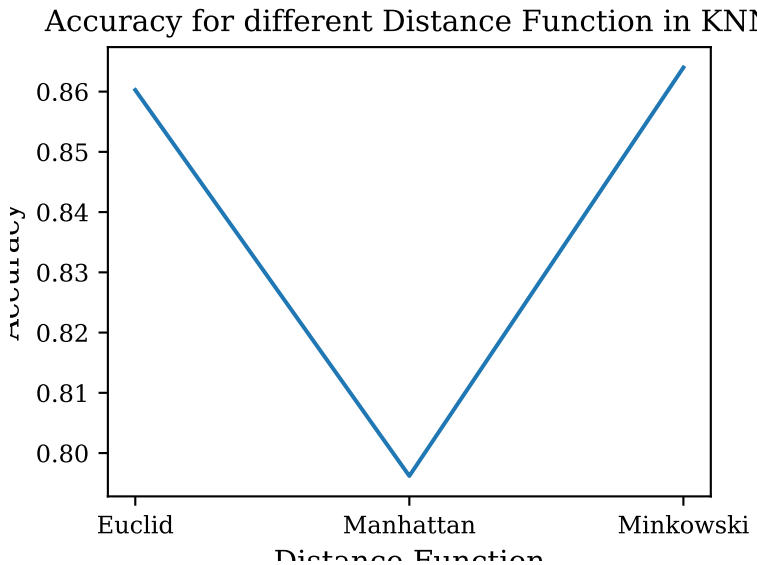
The peak of accuracy is achieved with k=5. Therefore all of the classifier will have k=5 from now on.

1.4 Is the best current k a good choice?

While it is a good indicator to choose the k, which has the best accuracy at the moment, it may not the best choice to test on new fresh images. As more images will be used to fit the classifier, new images come with many unseen properties or the distribution of classes can be changed. If we use the approach KNN, it should be a good practice to test out on different values of k, especially since k is not the only factor decides the accuracy of the model (for example the amount, quality and distribution of data also matters).

1.5 KNN with different distance metric

The Euclidean distance function is a specific case of Minkowski distance function with the scalar of 2. This time we test the accuracy of Euclidean metric compare to Manhattan metric (Minkowski with scalar of 1) and Minkowski metric with scalar of 3.



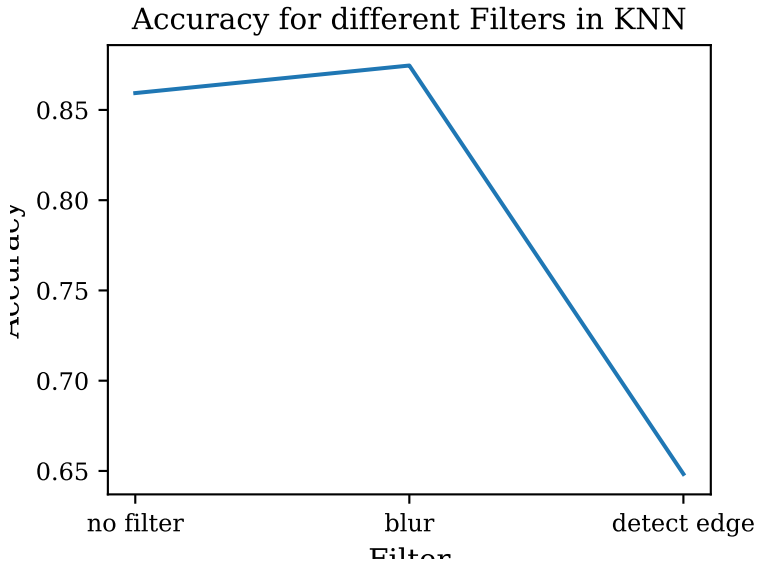
The result shown, the accuracy of Euclidean metric and 3-Minkowski metric are similar and Manhattan metric has a 6% lower in accuracy.

1.6 Feature Engineering

The convolutional operation is implemented in knn.py with the instruction presented in the task sheet.

1.7 Experiment with filters

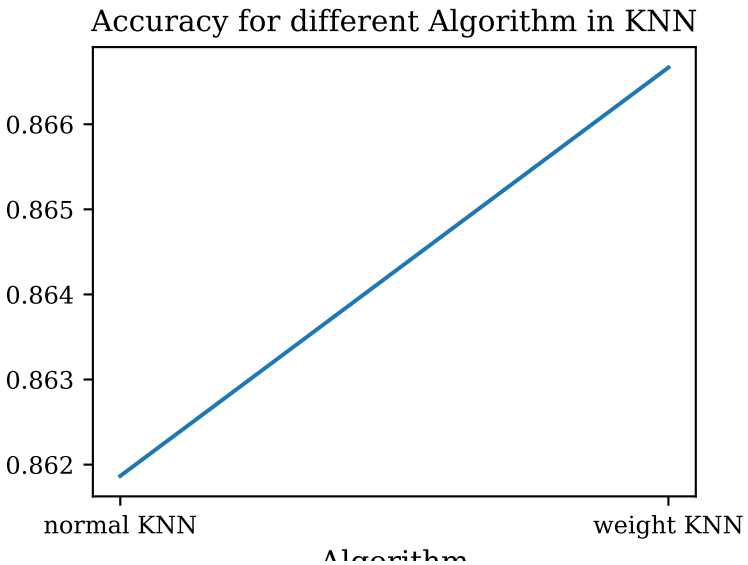
With the implemented convolutional operation, we test the classifier in 3 different cases (without filter, blur filter and edge filter) using 5-fold cross validation.



Blur filter improve our KNN-classifier a little while we have a significantly drop in accuracy with edge detection approach.

1.8 Weight KNN

Now we assigned weight into each neighbor, which is inversely proportional to the distance. This means the closer the neighbor to the test image, the more impact it will make to the result of the prediction. We modify our knn function with a new added parameter inverse_modifier to calculate the weight of each neighbor (inverse_modifier divided by distance)

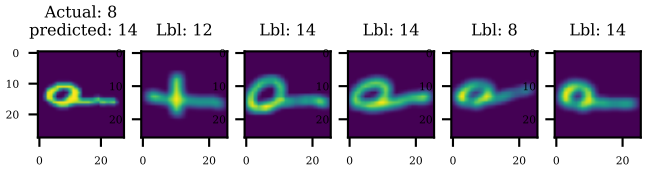


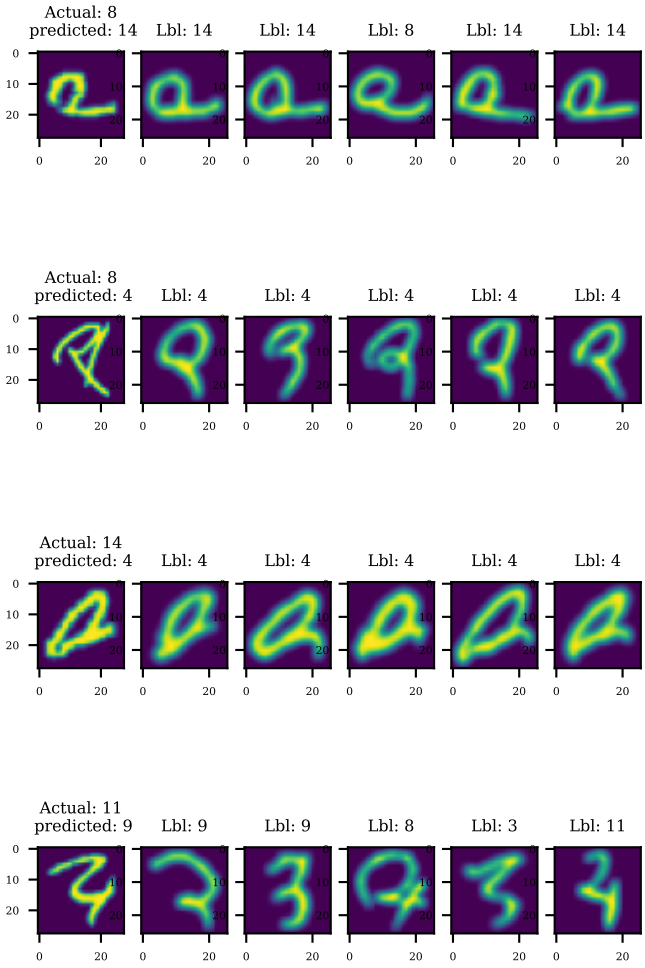
We find very small increment in accuracy with Weight KNN.

1.9 Misclassified samples

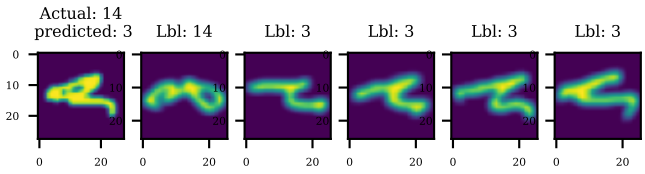
As the task sheet required, for at least three different distance measures and features obtained from two different filters, we plot the nearest neighbors to 5 random misclassifed samples. To fulfill the requirement, we plot 3 different cases.

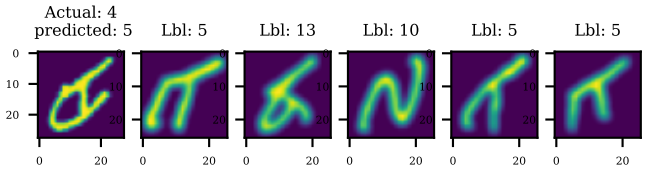
The first case is with a classifier with Euclidean distance metric and blur filter:

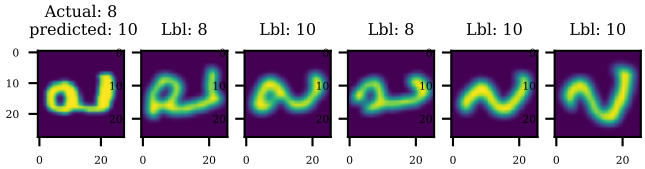


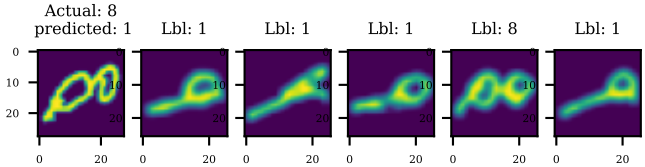


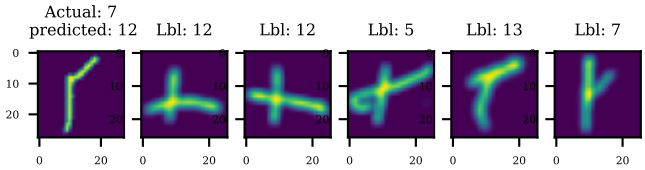
The second case is with a classifier with Manhattan distance metric and blur filter:



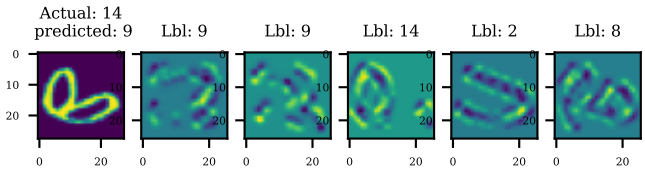


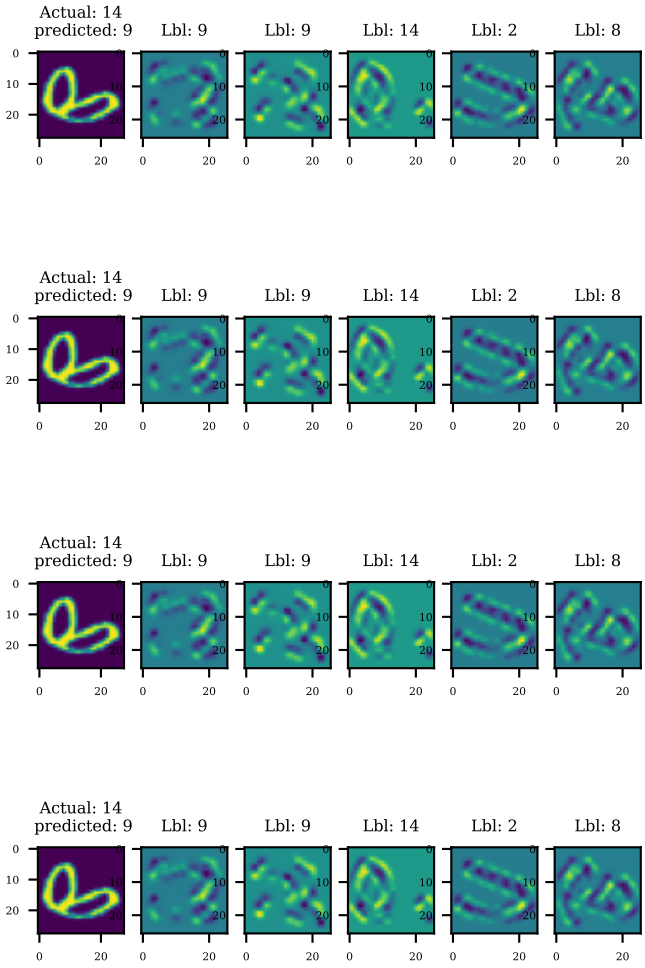






The third case is with a classifier with Manhattan distance metric and edge filter:





Many misclassified images has a very close pattern compare to their neighbors but the result of the predictions are still incorrect. Because we have many images of different classes that look identical to each other, many was predicted with the wrong label.