Additional work:

We will apply the same set of algorithms with hyper parameters tuned for MNIST to a second dataset: banknote authentication. The banknote authentication dataset consists of 1372 instances of data extracted from real and forged banknotes. The dataset can be found here: <http://archive.ics.uci.edu/ml/datasets/banknote+authentication#>

This dataset has 4 parameters and a binary target, the values for the parameters are extracted using Wavelet transform tools on digital images of real and forged banknotes.

(\*Need to provide some more background information on what parameters mean\*)

(\*If sufficient time, look into how different parameterizations of data affects prediction accuracy\*)

The parameters include:

1. Variance of wavelet transformed image
2. Skewness of wavelet transformed image
3. Kurtosis of wavelet transformed image
4. Entropy of image

Purpose:

We wish to explore how the algorithm perform across different but similar datasets, i.e. multitarget vs binary target classification, small vs large number of attributes. In addition to that, we wish to gain insight into how hyperparameter tuning improves performance of an algorithm across multiple datasets vs performance improvement on individual dataset. i.e. after tuning for MNIST dataset, does the same set of hyperparameters work just as well for banknote authentication and vice versa?

Results:

Performance with hyperparameters tuned for MNIST:

Algorithm (performance of banknote authentication) / (performance of MNIST):

KNN:

Logistic Regression:

Lenet:

Performance with hyperparameters tuned for bank note authentication:

Algorithm (performance of MNIST) / (performance of banknote authentication):

KNN:

Logistic Regression:

Lenet:

Conclusion:

(Give some explanation/hypothesis based on results obtained above)

e.g. how hyperparameters improve overall algorithm efficacy vs dataset specific accuracy.