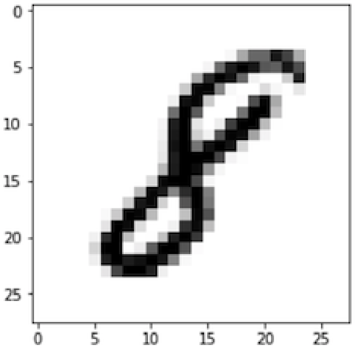
1) Introduction

2) Clear description of dataset and algorithms used

The dataset used in this project is the infamous MNIST dataset[1]. The MNIST dataset consists of 70000 28x28 pixelated images of handwritten numbers. Each image can be represented as a 28x28 matrix with each element containing a value between 0 and 1 representing the darkness of the pixel. Alternatively, the 28x28 matrix can be transformed into a 784x1 vector array for easy processing. The 28x28 representation technically contains more useful information since it conserves pixel proximity, but for this project, I use 784x1.



Preprocessing is an important step to building a classifier. Thankfully, the MNIST dataset is well known for requiring little-to-no preprocessing to test machine learning algorithms https://medium.com/tebs-lab/how-to-classify-mnist-digits-with-different-neural-network-architectures-39c75a0f03e3. For this reason, preprocessing was avoided in order to focus on algorithm implementation. Similarly, cross-validation can result in a more-robust assessment but is not necessary for achieving tangible results with the MNIST dataset.

MNIST designates 60,0000 of the 70,000 images as "training" images and 10,000 images as "testing" images. For this project, the 60,000 "training" images are used as my training dataset and the 10,000 "testing" images are used as my validation dataset.

Various algorithms were deployed to predicting the

Regression and support-vector machines

Loss Function	**Regularization**	**Fitting Degrees**
Least squares	L1	0, 1, 2
	L2	0, 1, 2
Hinge	L2	0, 1, 2
Squared hinge	L1	0, 1, 2
	L2	0, 1, 2

Neural Networks

Loss Function	**Activation**	**No. Hidden Layers**
Least squares	relu	1, 2
	sigmoid	1, 2
Categorical cross-entropy	relu	1, 2
	sigmoid	1, 2

Regression

Least-squares loss, l1 regularized, (0, 1, 2 degree)

Least-squares loss, l2 regularized (0, 1, 2 degree)

Hinge loss, l2 regularized (0, 1, 2 degree)

Squared Hinge loss, l1 regularized (0, 1, 2 degree)

Squared Hinge loss, l2 regularized (0, 1, 2 degree)

Neural Network

Least squares loss

- relu activation functions
  - 2 layers, 3 layers

sigmoid activation function

2 layers, 3 layers

Categorical cross-entropy loss

relu activation functions

2 layers, 3 layers

sigmoid activation function

2 layers, 3 layers

3) Results (tables figures and discussion)

Loss Function	Activation	No. Hidden Layers
Least squares	relu	1, 2
	sigmoid	1, 2
Categorical cross-entropy	relu	1, 2
	sigmoid	1, 2

4) Strengths and limitations

Performance could likely be improved by centering and scaling images or by splitting the “7” class into two separate classes, one where class contains 7’s with the central cross (7“ink free” font) and one class is without the central cross (7).

Loss Function	Regularization	Fitting Degrees
Least squares	L1	0, 1, 2
	L2	0, 1, 2
Hinge	L2	0, 1, 2
Squared hinge	L1	0, 1, 2
	L2	0, 1, 2

5) conclusion

Loss Function	Regularization	Fitting Degrees
Least squares	L1	0, 1, 2
	L2	0, 1, 2
Hinge	L2	0, 1, 2
Squared hinge	L1	0, 1, 2
	L2	0, 1, 2