



FRUIT CLASSIFICATION USING CNN

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Introduction

- Image Classification using Convolutional Neural Network (CNN)
- Fruit Classification Network
- Utilized Python and Pytorch on 1 GPU

Application

- Automate Customs and Border Protections (CBP) processes for use in agriculture industry
- In 2018, CBP apprehended 2.5 tons of prohibited fruit in Ohio
- Prohibited due to disease and pest control measures
- CBP officers inspect fruit by hand
- Deep Learning could aid in the inspection with higher rates of inspection

Data

- Fruits 360 Dataset | Kaggle: <https://www.kaggle.com/moltean/fruits/version/2>
- 20,000 images with 33 classes of fruit
- Images are full-color and 100 x 100 pixels
- Training set: 15,506 images
- Testing set: 5,195 images
- Ran two networks
 - *Subset – 5 fruits*
 - *Entire set – 33 fruits*

Fruit Images

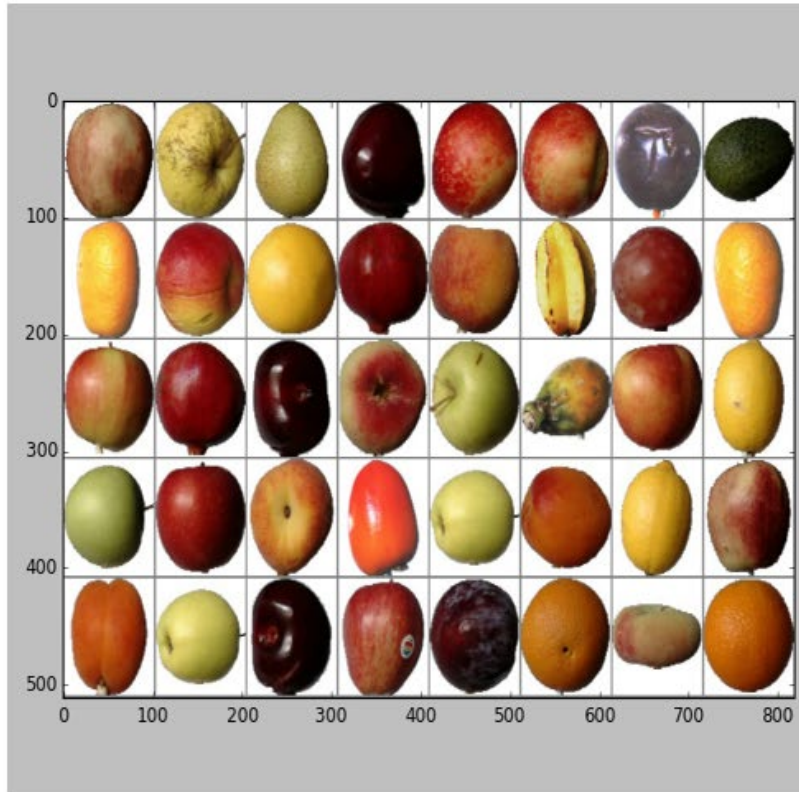


Figure 1. Mini batch of data from overall dataset

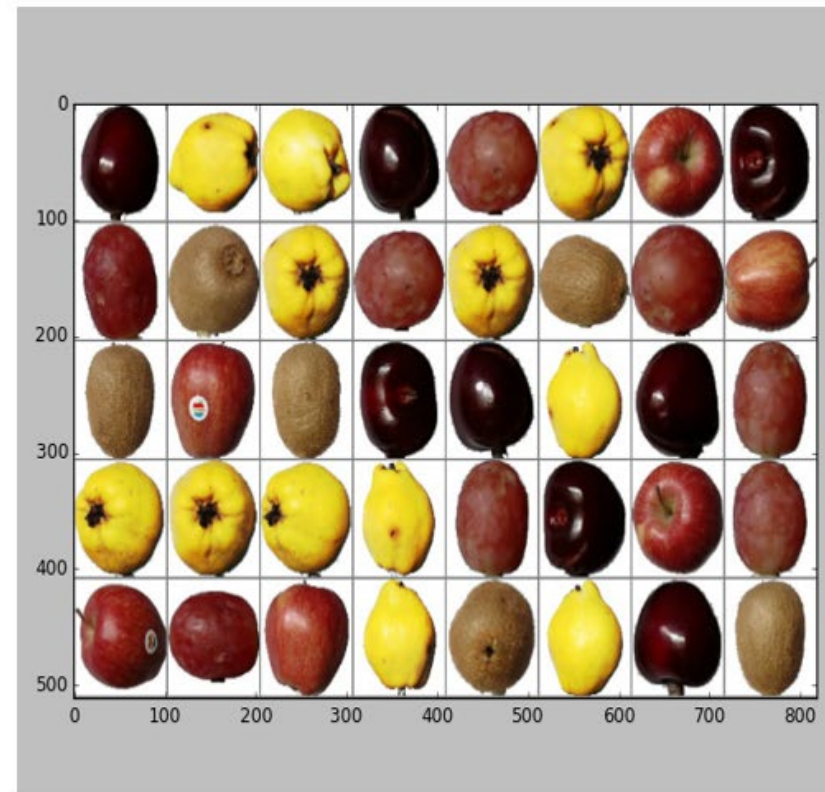


Figure 2. Mini batch from fruits_data_subset

Network

- 2-dimension architecture
- BatchNorm2D
- Non-linear activation function – ReLU
- ADAM optimizer
 - *Computes individual learning rates for different parameters*

Code

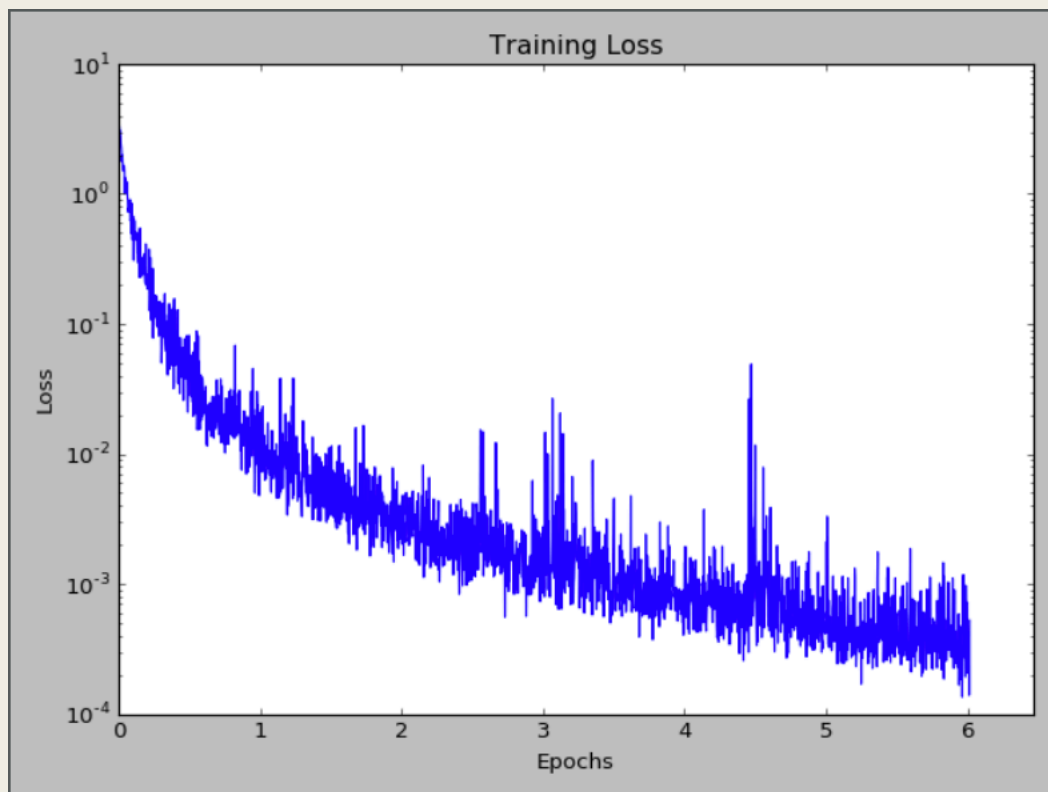
```
class CNN(nn.Module):
    def __init__(self):
        super(CNN, self).__init__()

        self.layer1 = nn.Sequential(
            nn.Conv2d(in_channels=3, out_channels=32, kernel_size=5, padding=2),
            nn.BatchNorm2d(num_features=32),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2))

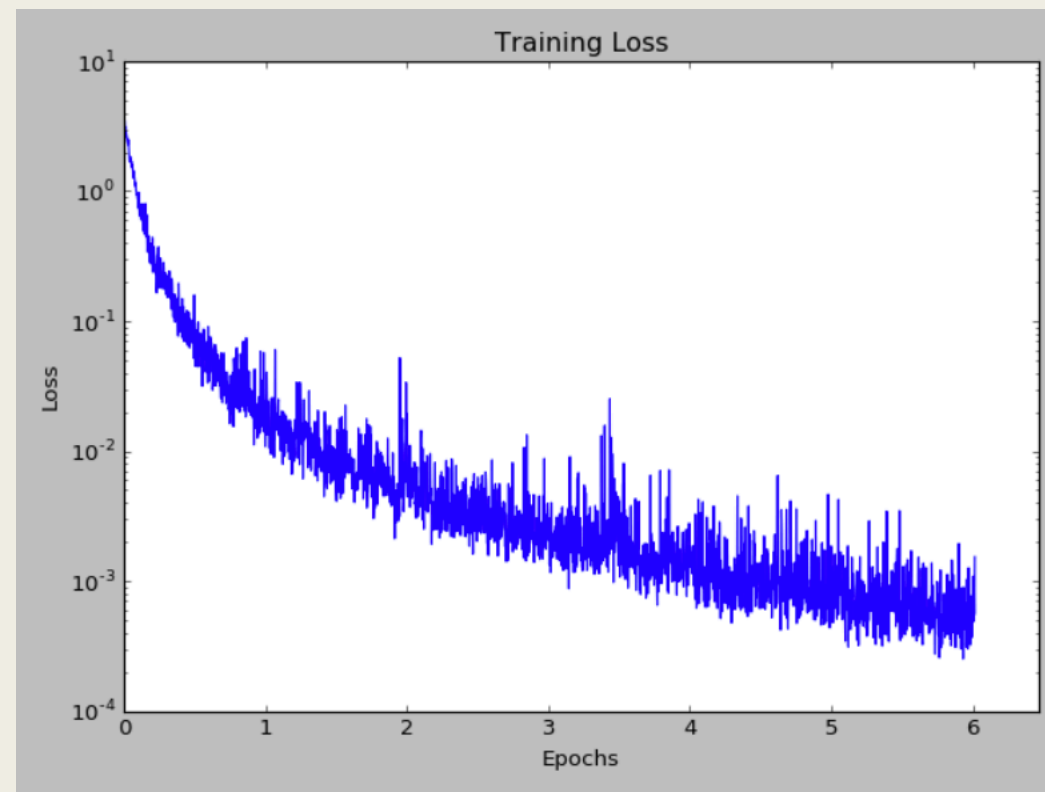
        self.layer2 = nn.Sequential(
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=5, padding=2),
            nn.BatchNorm2d(num_features=64),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2))

        self.fc = nn.Linear(in_features=40000, out_features=num_classes)
```

Training Loss

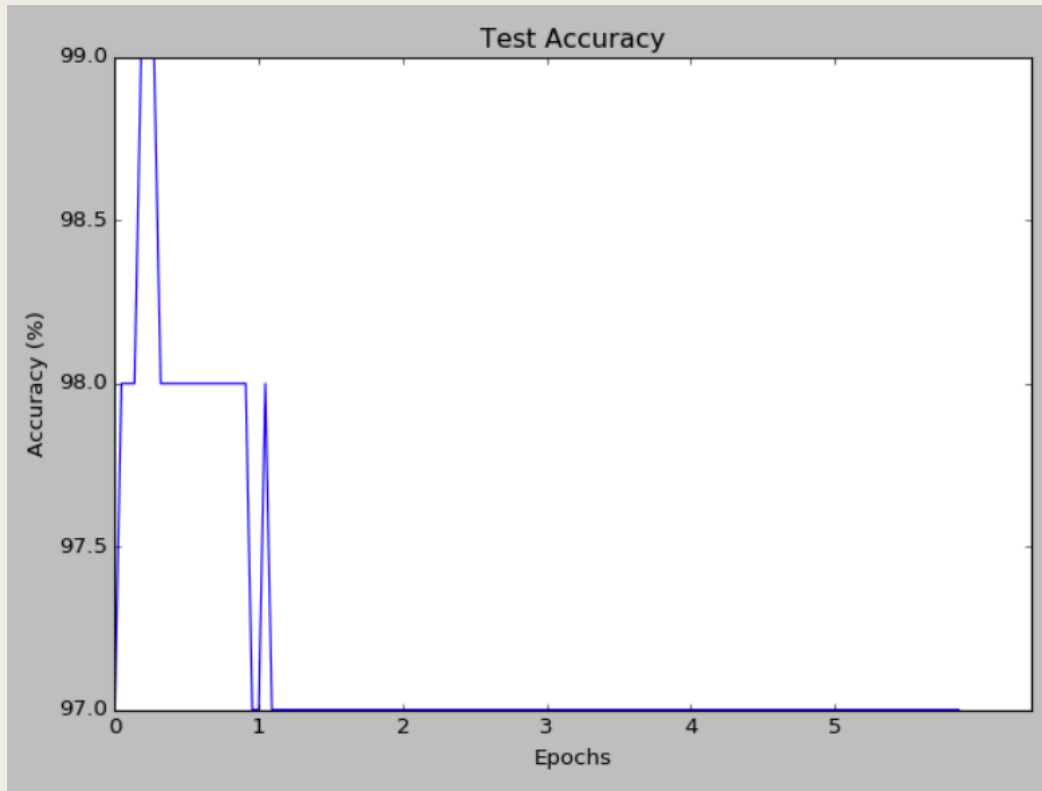


2 Layer Loss

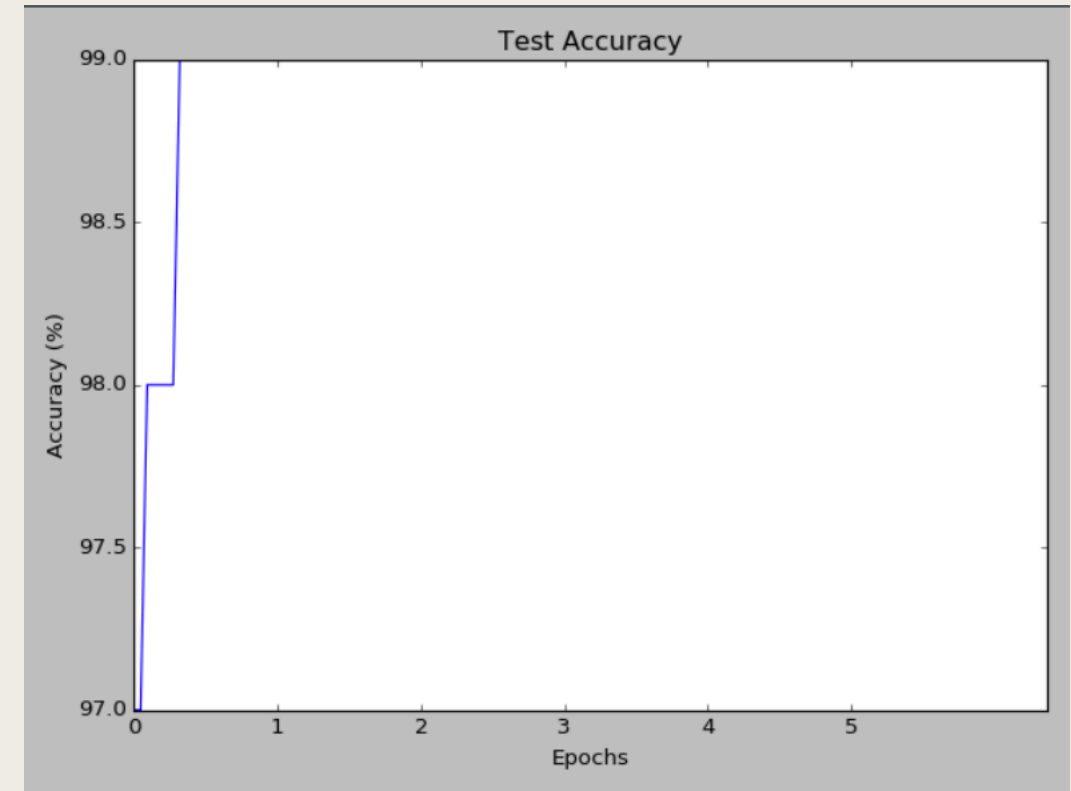


3 Layer Loss

Results – Accuracy



2 Layer Accuracy – 97%



3 Layer Accuracy – 99%

Results – Confusion Matrix

	Apple Red 1	Cherry	Grape	Kiwi	Quince
Apple Red 1	164	0	0	0	0
Cherry	0	164	0	0	0
Grape	0	0	164	0	0
Kiwi	0	0	0	156	0
Quince	0	0	0	0	166

Figure 3. Confusion matrix for fruit_data_subset

	Apple Red 1	Apple Red Yellow	Braeburn	Cherry	Golden 3	Granny Smith	Nectarine	Peach
Apple Red 2			10					
Braeburn							36	
Nectarine		19						13
Peach	17							
Pear					26	4		
Plum				11				

Figure 4. Number of Misclassifications

















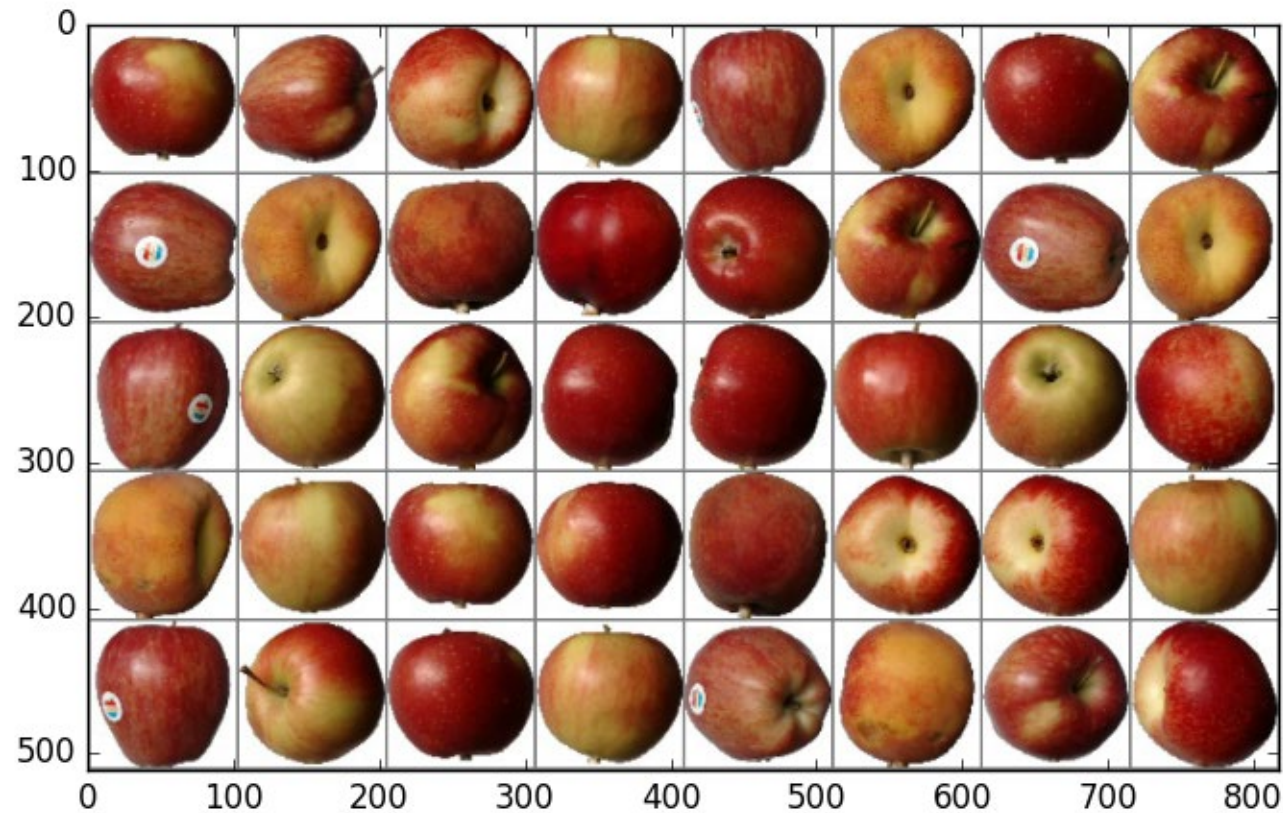
Red Apple 1	Peach	Apple Red Yellow	Nectarine
			
Number of misclassifications = 17		Number of misclassifications = 19	
Pear	Golden 3	Pear	Granny Smith
			
Number of misclassifications = 26		Number of misclassifications = 4	
Apple Red 2	Braeburn	Braeburn	Nectarine
			
Number of misclassifications = 10		Number of misclassifications = 36	
Nectarine	Peach	Cherry	Plum
			
Number of misclassifications = 13		Number of misclassifications = 11	

Figure 5. Fruit Misclassifications, 2-Layer Network

Can You Tell the Difference?



Conclusion

- Deep Learning was accurate between 97 and 100 percent in classifying fruits
- Government and industry have job processes that are ripe for disruption
- CNN and ADAM optimizer were the correct choices for our model



QUESTIONS?