# Classifying Prescription Medication

BY: **JOEY** CHAO

# Introduction

- Prescription drug usage is on the rise as the population ages. Roughly 7 in 10 Americans regularly take prescription medication, and this number continues to grow.
- A patient may need to take between 1 and 5 pills a day.
- With so many pills that share similar appearances, it is easy to mix up different medications— a potentially deadly mistake.
- What if we could create an app that uses a smartphone camera to automatically detect a drug?

# Introduction

**Purpose**

Recognize images of Rx medications by shape and brand name.

**Approach**

Use Keras and FastAi libraries to build a deep learning model.

**Data**

Images of medications obtained from Google and the NIH database.

# Collecting Data

- Pillbox database (https://pillbox.nlm.nih.gov/developers.html)
    - Database of 8000+ Rx images + CSV file of description, medication information, and corresponding image file names.
- Scraped Google Images
- Inspect images, remove corrupted files, and validate class.
- Organized images into folders based on prescription name and shape.

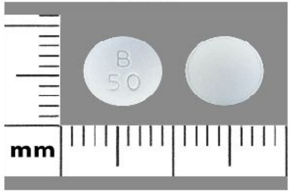
# Visualizing the Data - Pill Shapes

Round


Round


Round


Round




Round


Oblong

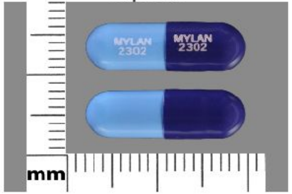

Oblong


Oblong

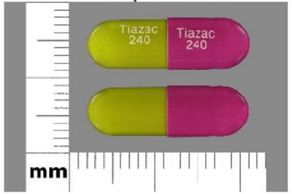

Oblong


Oblong


Capsule



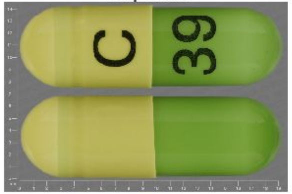

Capsule



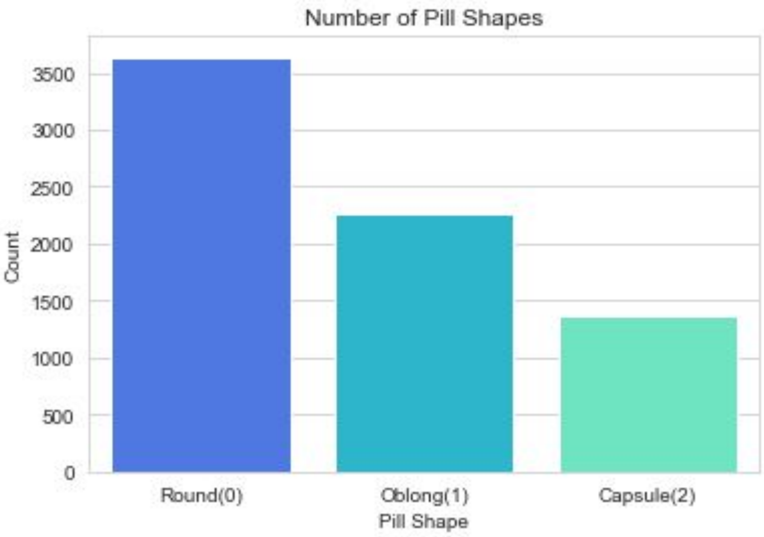

Capsule


Capsule


Capsule



# Visualizing the Data - Pill Shapes




- Total of 7278 pills were labelled either round, oblong or capsule.
- Slight class imbalance.
- There are some ambiguously labelled pills.


# Data Augmentation

Gathering images was a major wall— lack of variety of images for specific medication made training Neural Networks difficult.

To generate more data, I zoomed, rotated, and changed the brightness/backgrounds of each image randomly.

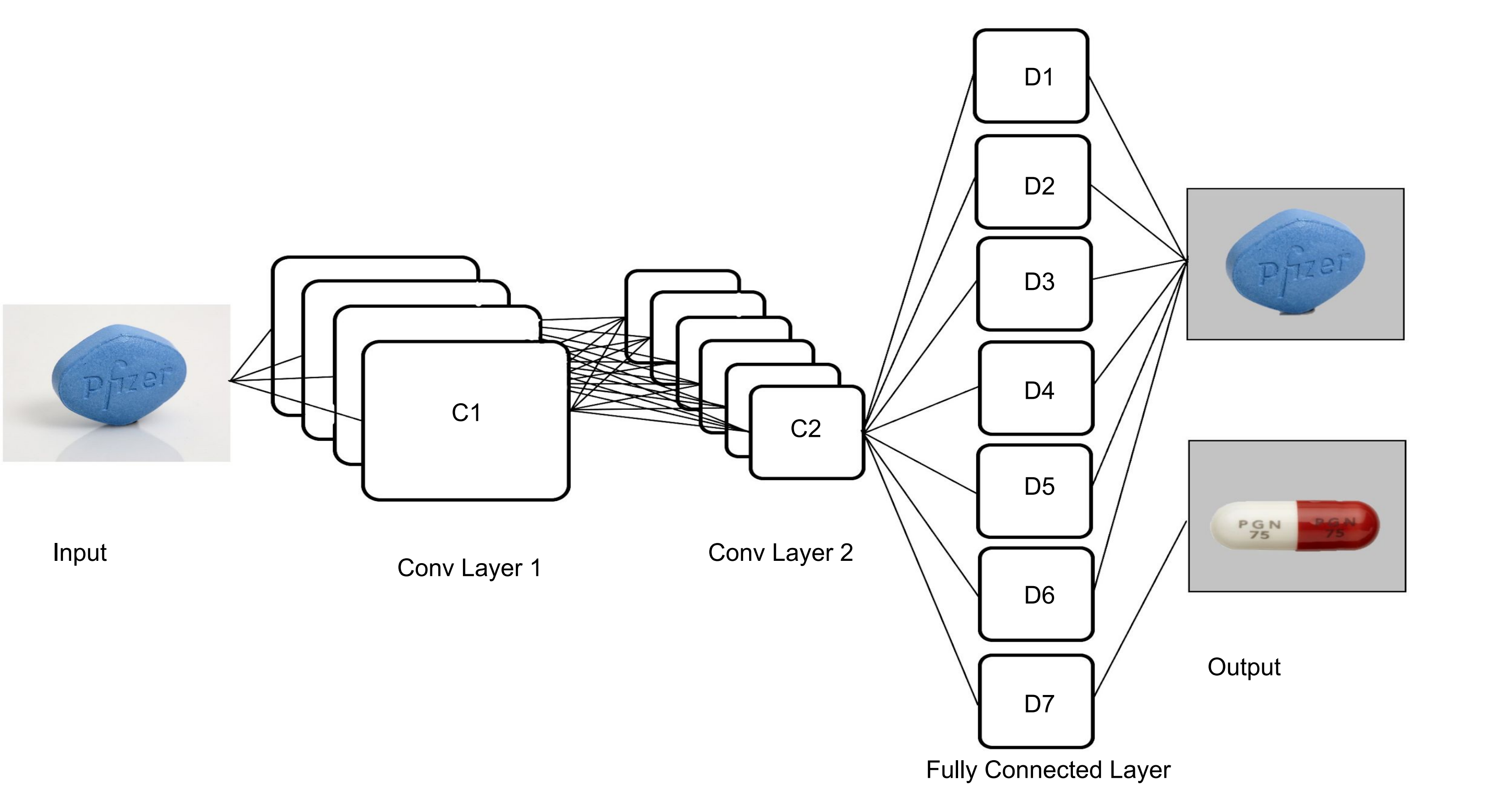
Original


BG/Color Augment


Rotated


BG/Zoom Augment

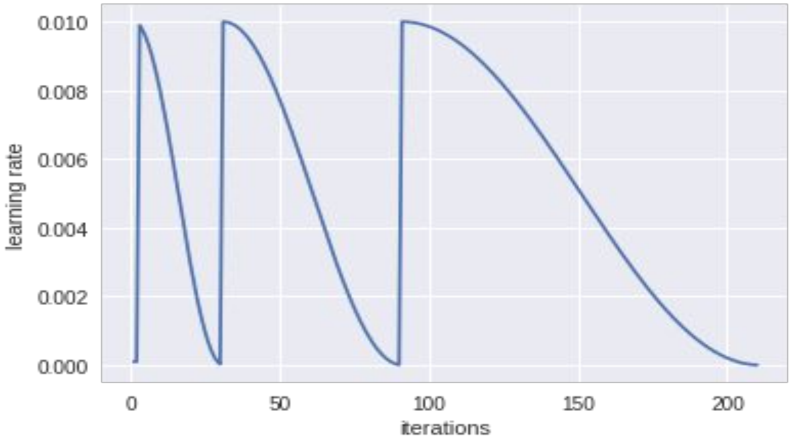
# Convolutional Neural Networks



# Classifying Pills by Shape

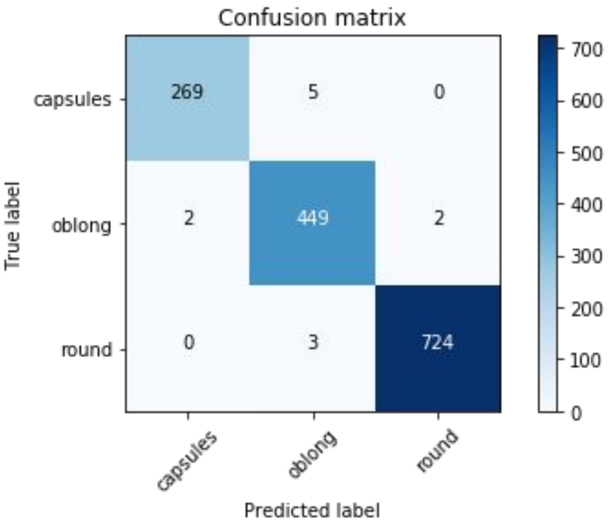
- Leverage Resnet 34’s efficient architecture and base weights to train on drug dataset.
- Chose base learning rate based on Learning Rate vs Loss plot.
- Varied the learning rate by layer.
  - Lower learning rates were used by earlier layers
  - Adjusted length of each cycle
- Model was 99.3% accurate.

# Differential Learning Rate


- Learning rate is how much a model is adjusting the weights while trying to find the minimum loss.
- I chose a learning rate of .1 because the loss is still decreasing at that point.
- Differential learning rate is adjusting learning rate based on layers of the Neural Network.
    - 1e-3 for early layers
    - 1e-2 for middle layers
    - 1e-1 for later layers
- Varied the cycle length and learning rate to achieve a more stable solution.

# Visualizing the Results



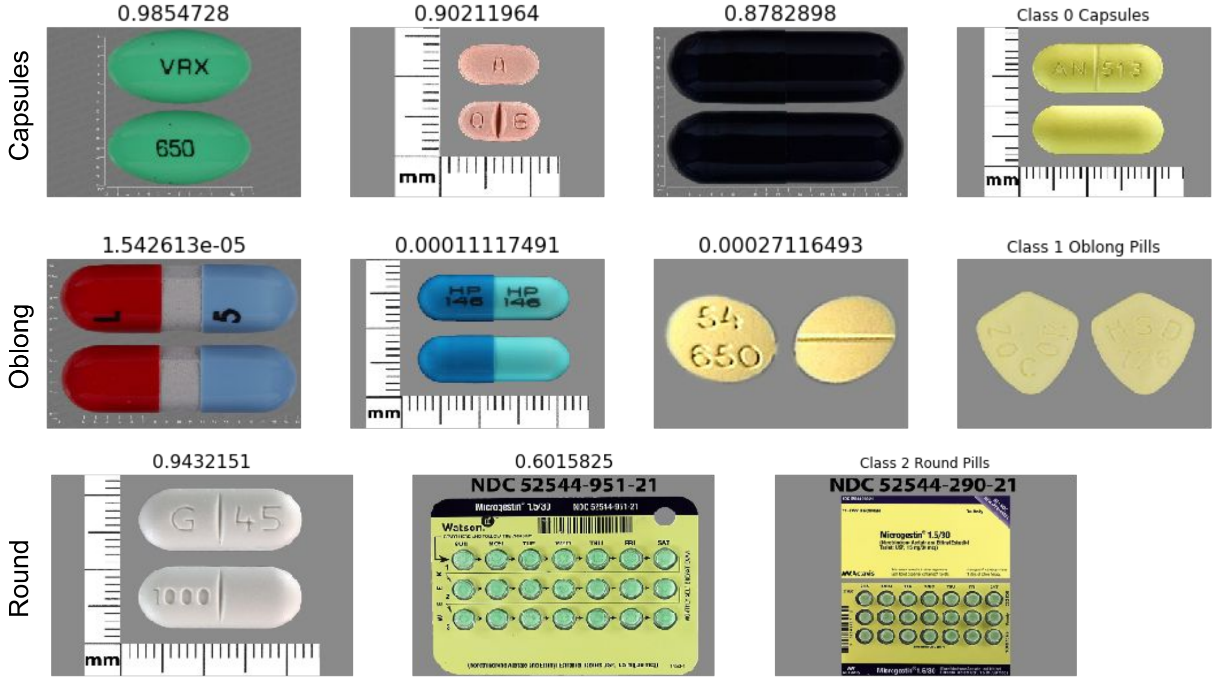

Most Correct Predictions

# Visualizing the Results- Continued

The images to the right show the most incorrectly labelled pills.

- Some items in this list were originally mislabelled
- Some items are ambiguous and can belong to multiple classes.

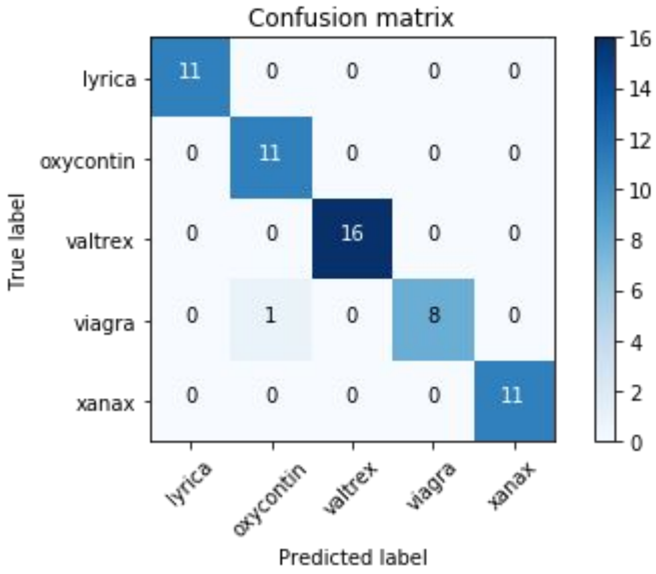
Overall, the model did a good job predicting Rx shapes!

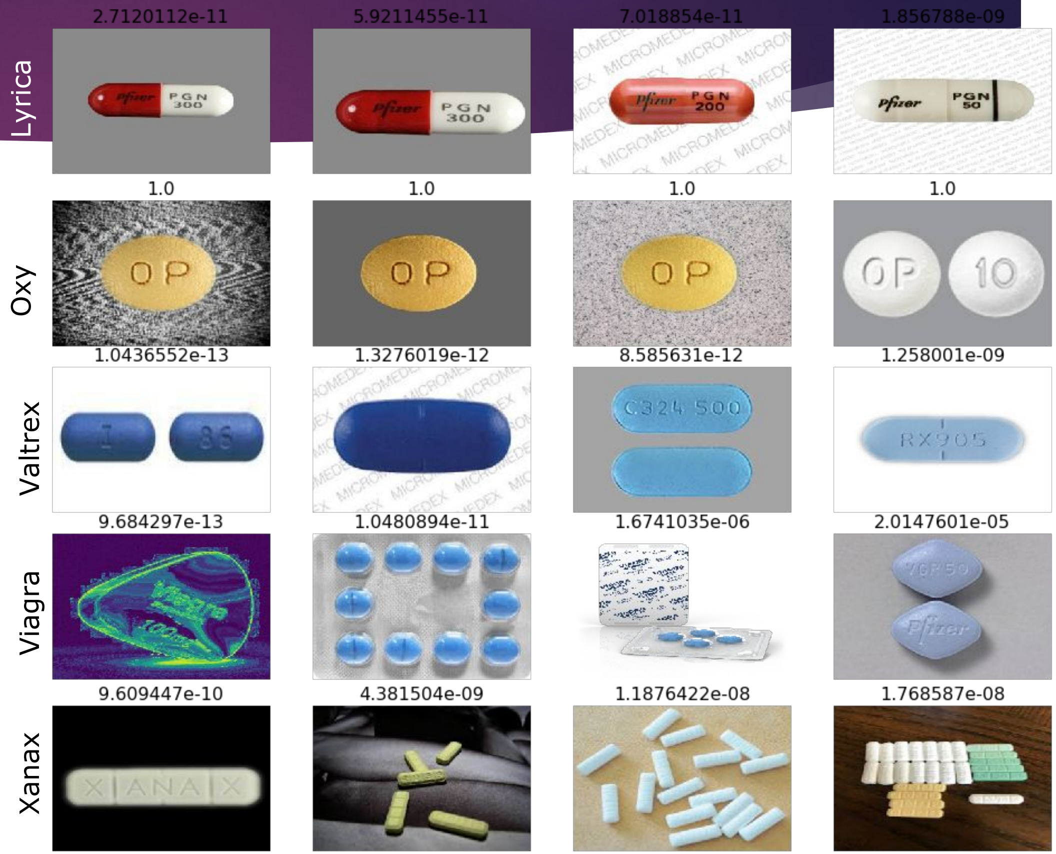


# Convolutional Neural Network with FastAi

- Picked 5 branded Rx medications with a variety of easily accessible images.
    - Lyrica, Xanax, Oxycontin, Viagra, and Valtrex
- Images were inspected to make sure they had the correct pill.
- Augmented dataset with randomly zoomed, blurred, brightened, and rotated pictures.
- Added different backgrounds by utilizing cv2 library edge detection features to get the mask.
- Validation Accuracy of 98.3% but I suspect overfitting problems.

# Visualizing the Results



# Visualizing the Results

## Most Uncertain

0.3533911


0.22032833


0.14793459

0.04217729

## Most Incorrect

1.6153951e-08


- Validation data size was relatively small because I couldn’t find more images.
- The only incorrectly labelled medication is not one of the 5 classes.
- The last 2 images of the most uncertain make sense. It is hard for humans to even distinguish the medications.
- The first 2 images are clearly Valtrex. The background noise potentially lowered confidence.

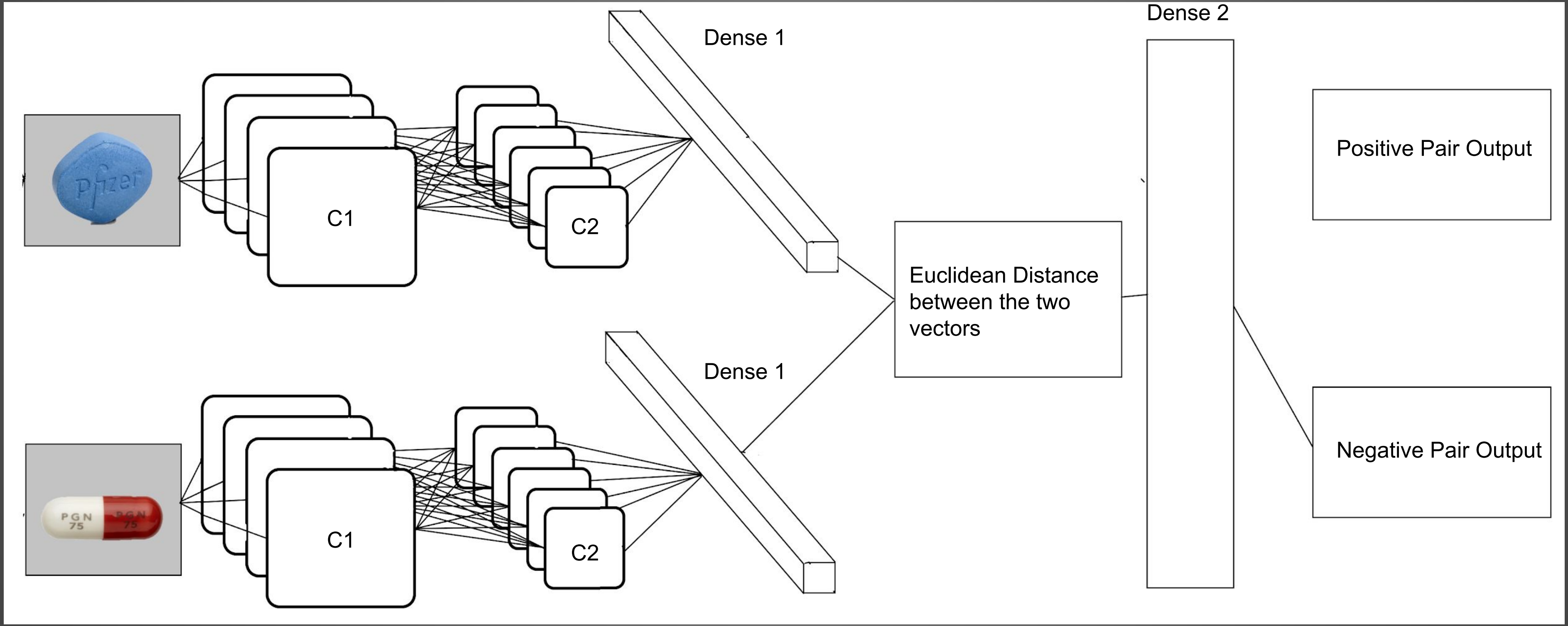
# Complications

- The FDA has approved more than 1500 New Molecular Entities since 1930[1]
- Each drug may have 1-10 different dosage forms and 5-20 manufacturers creating generics after patent expirations.
- This creates an enormous amount of distinct medications that are often similar in color, shape, size, and dosage form.
- Neural Networks have become extremely accurate, but they often require thousands of images per class to perform well.
- I didn’t have access to a large quantity of unique images which led to overfitting of the model.

# Siamese Neural Networks

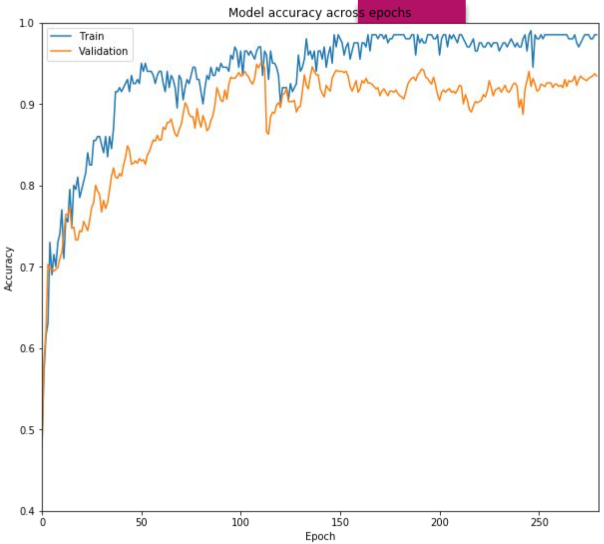
- Siamese Neural Networks consist of 2 identical neural networks with a different image passing through both (same weights and same architecture).
  - I used ResNet34 as the pre-trained architecture.
  - The Euclidean distance is then calculated between the output pair and fed into dense layer.
  - Images of the same class will have a smaller distance and the pair will be classified as being the same class.
- I used Siamese Neural Networks to attempt a one-shot learning solution that could deal with limited examples.
- Created equal sets of positive and negative class pairs.

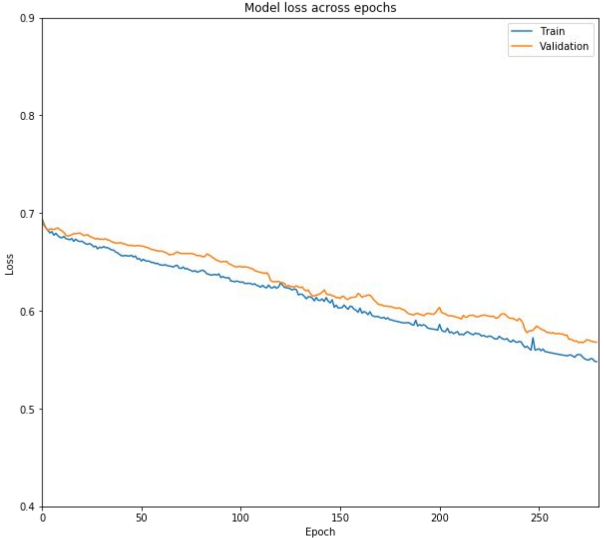
# Siamese CNNs



# Results

- 93.43% accuracy achieved.
- Validation loss reached a maximum around 280 epochs.
- In the case of Siamese Networks, the outcome is binary— either a positive pair or negative pair.



# Results- Incorrect predictions

It is interesting to see some of the incorrect predictions.

The classifier predicted these pairs were the same.

Interestingly the angles of the pills seem to be the same, and the sizes are similar.

Increasing resolution to clear up the lettering may increase accuracy.

# Future Work

- I only trained the model with a hand full of images I could obtain. More images from consumers can help contribute to a robust model with higher accuracy.
- An ensemble of Neural Networks can help to improve performance while reducing overfitting.
- Siamese networks seem promising. A future implementation can create input pairs by taking test image and pairing it with images of all classes to predict the positive pair.

# Thank you!