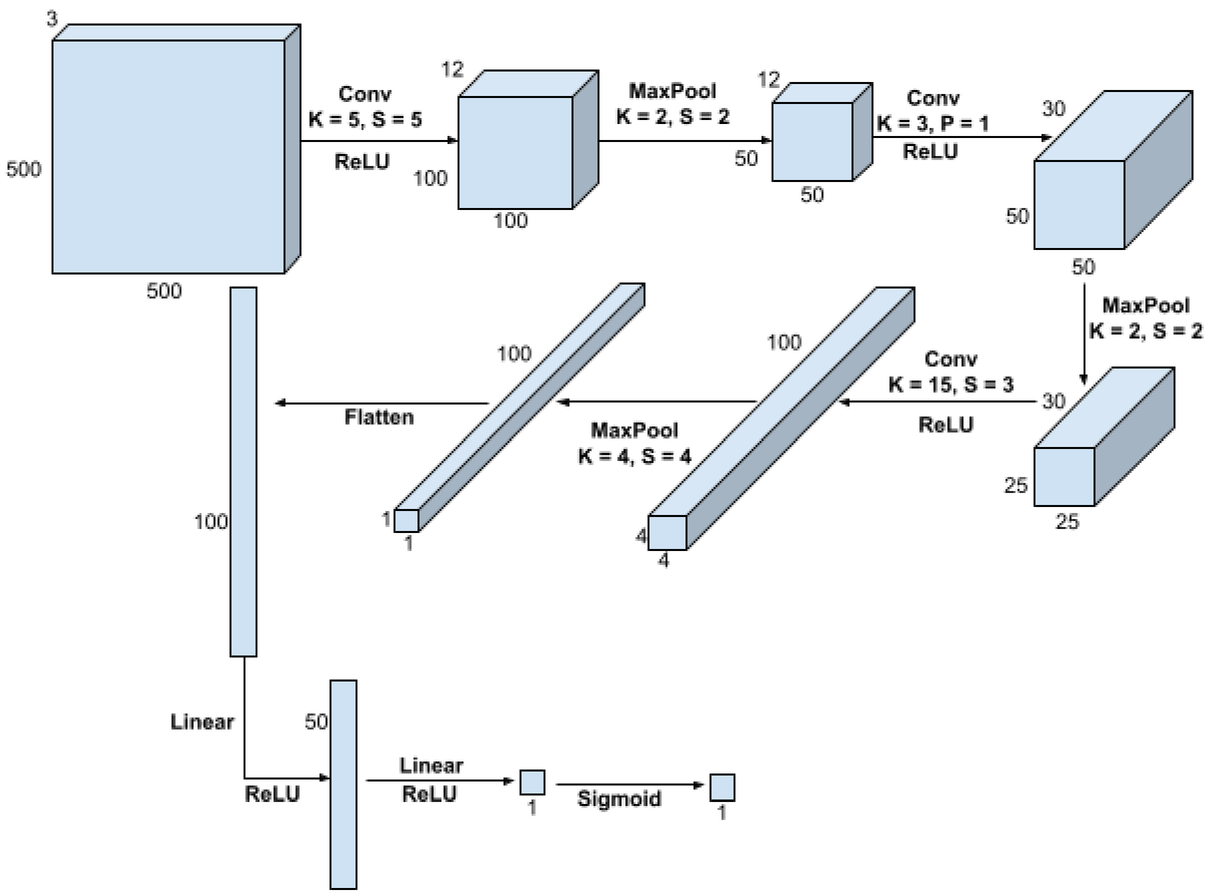
MSAI-437: Deep Learning

Homework 2 (Group 9)

Convolutional Neural Network

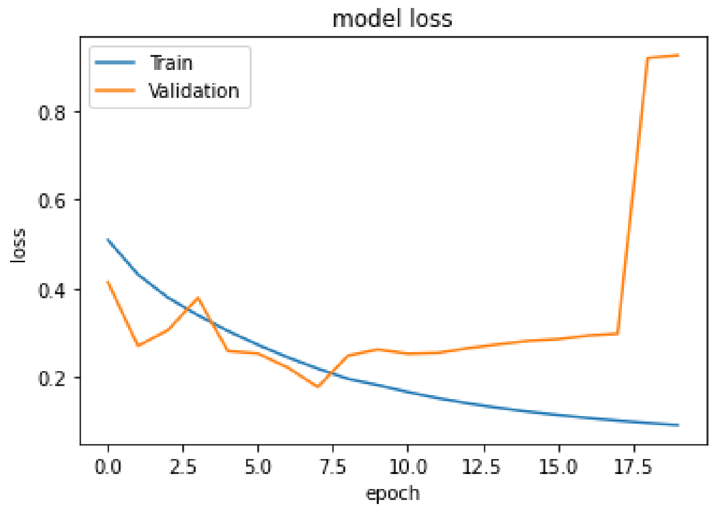
Architecture



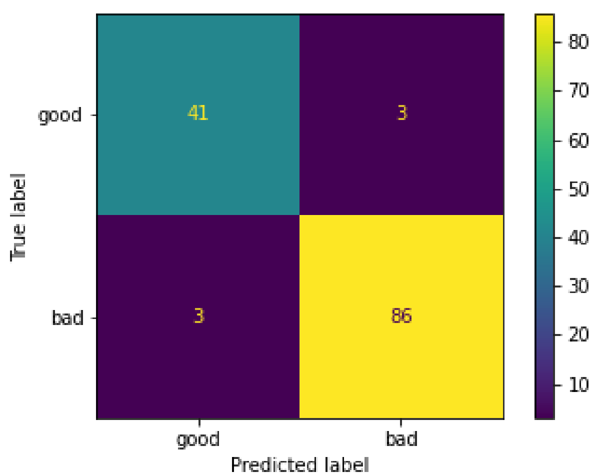
Hyperparameters

- **Loss Function:** Binary Cross-Entropy
- **Optimizer:** Adam Optimizer
- **Learning Rate**: 0.001
- **Number of Training Epochs**: 20

Learning Curves



Validation Set Performance



Validation accuracy = 0.9549

Limitations

The main limitation of our CNN is that it is unable to represent spatial information about the features it is extracting. This can cause issues because if certain filters are mainly contributing to the unhealthy classification and that feature is found in the background of a healthy leaf, the image will be classified incorrectly. The CNN has no way of saying “This feature should be found near the center of the image (where the leaf is).”

Autoencoder

Methodology

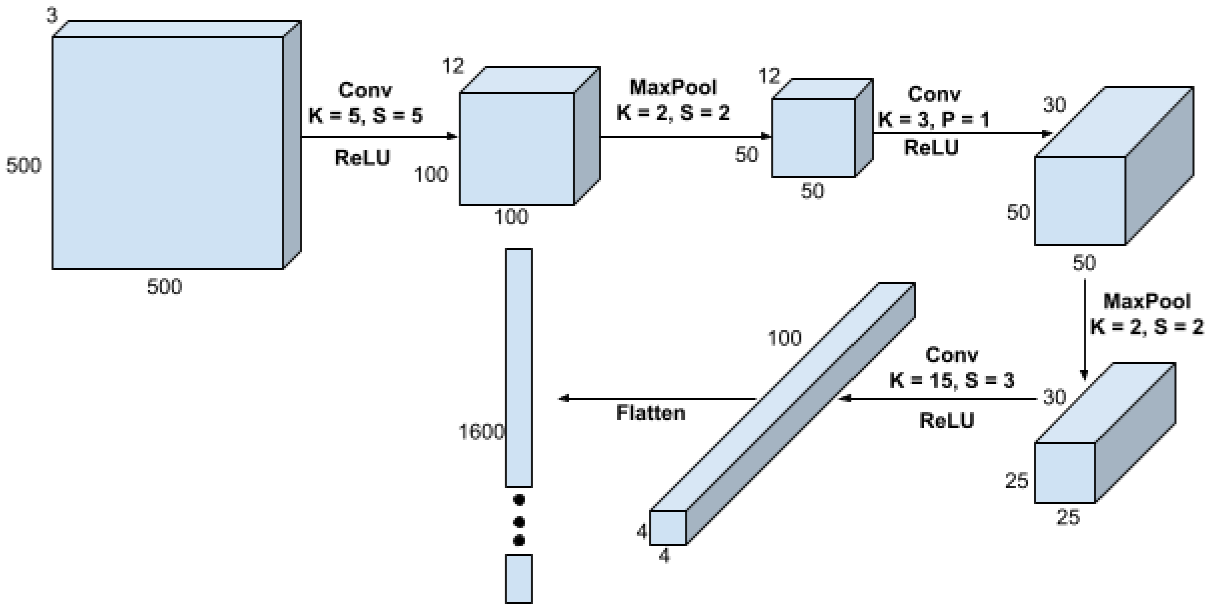
We trained the autoencoder on the Beans dataset using only the healthy leaves. We used the input images themselves as labels, and minimized the Mean Squared Error. The encoder condenses the 3x500x500 image into a 1x1600 latent space.

Once the autoencoder was trained, we discarded the decoder half of the architecture (see next two pages), retaining only the encoder.

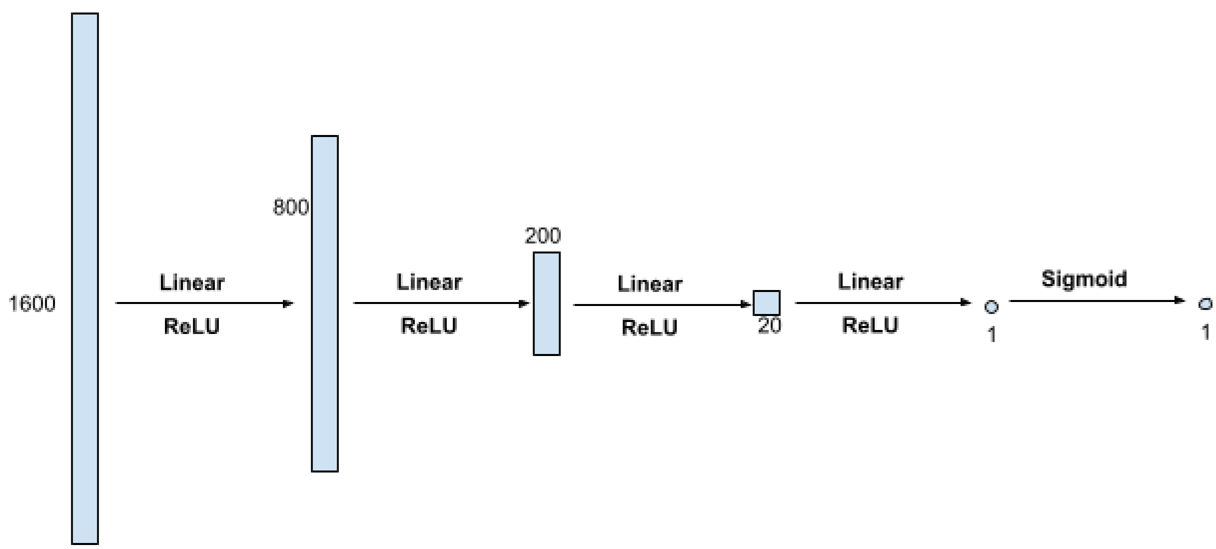
We then used a feed forward neural network (FFNN) to classify the Beans dataset. We passed all the images through the encoder to create a 1x1600 vector. It was then just a simple matter of running a FFNN on the 1x1600 vector for classification into healthy or unhealthy. We used Binary Cross Entropy as the loss function.

Architecture

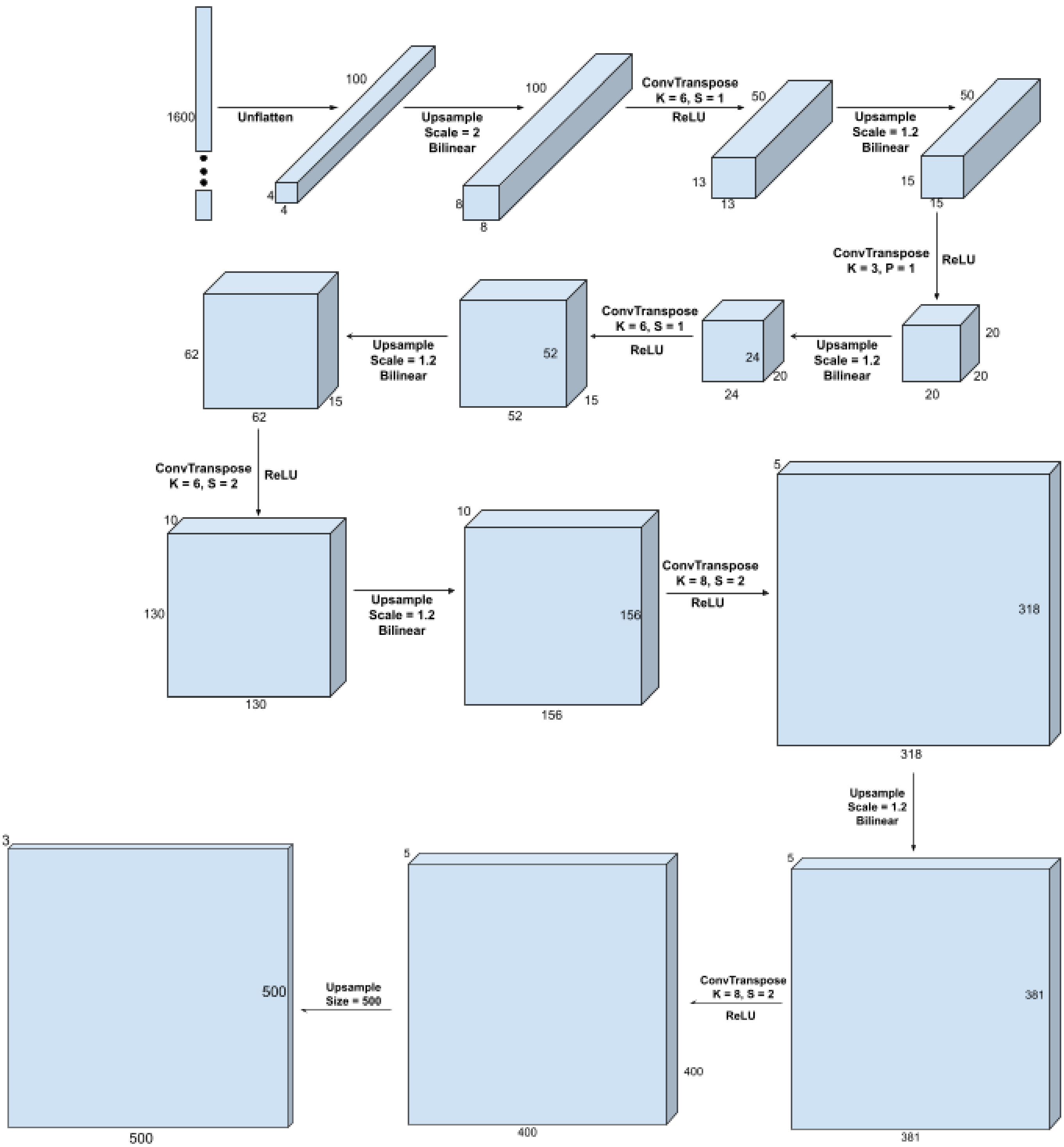
Encoder



Feed Forward Neural Network



Decoder


1600
Unflatten
100
4
4
Upsample
Scale = 2
Bilinear
100
8
8
ConvTranspose
K = 6, S = 1
ReLU
50
13
13
Upsample
Scale = 1.2
Bilinear
50
15
15
ConvTranspose
K = 3, P = 1
ReLU
20
20
20
Upsample
Scale = 1.2
Bilinear
24
20
24
ConvTranspose
K = 6, S = 1
ReLU
52
15
52
Upsample
Scale = 1.2
Bilinear
62
15
62
ConvTranspose
K = 6, S = 2
ReLU
10
130
130
Upsample
Scale = 1.2
Bilinear
10
156
156
ConvTranspose
K = 8, S = 2
ReLU
5
318
318
Upsample
Scale = 1.2
Bilinear
5
381
381
ConvTranspose
K = 8, S = 2
ReLU
5
400
400
Upsample
Size = 500
3
500
500

Hyperparameters

Autoencoder

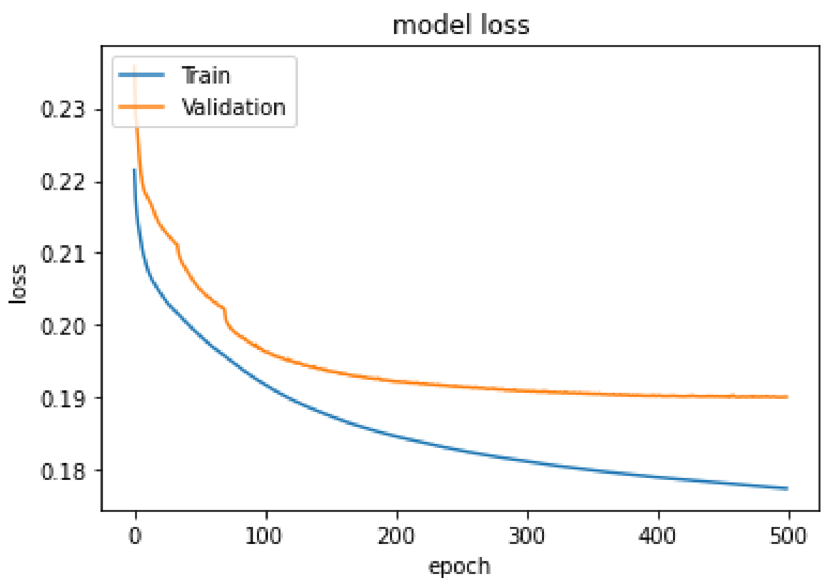
- **Loss Function:** Mean Squared Error
- **Optimizer:** Adam Optimizer
- **Learning Rate**: 0.00001
- **Number of Training Epochs**: 500

Feed Forward Neural Network

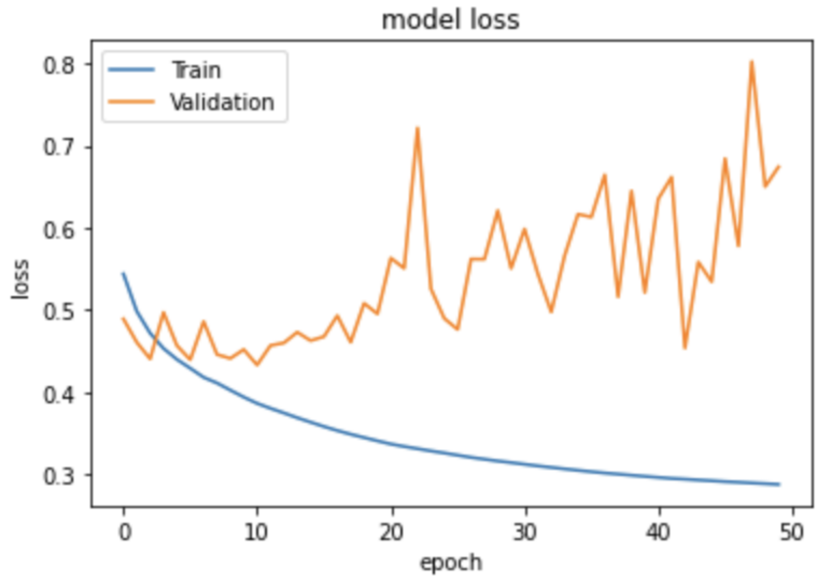
- **Loss Function:** Binary Cross-Entropy
- **Optimizer:** Adam Optimizer
- **Learning Rate**: 0.0001
- **Number of Training Epochs**: 100

Learning Curves

Autoencoder

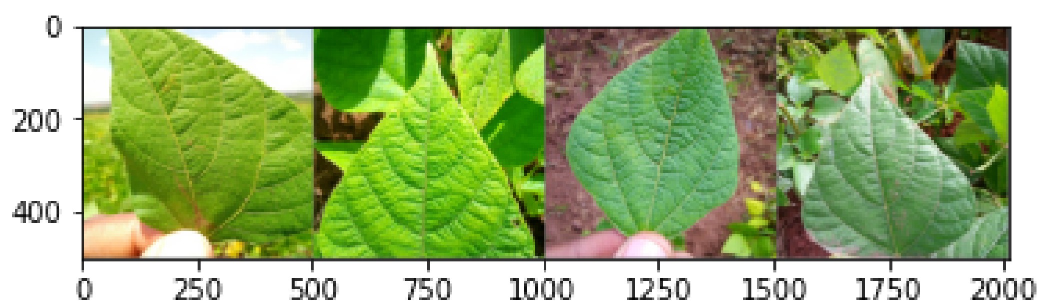


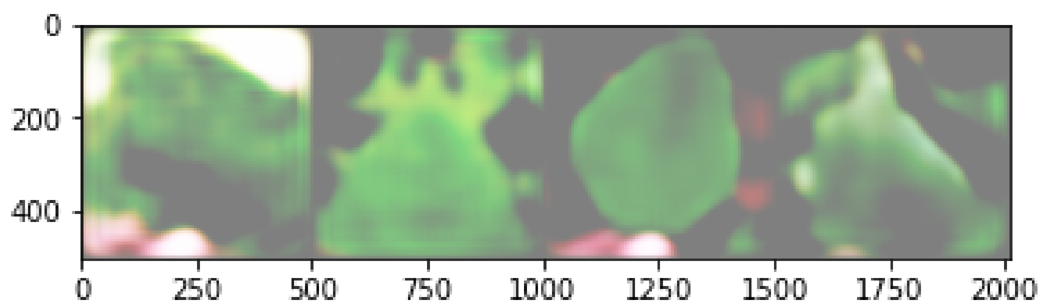
Feed Forward Neural Network



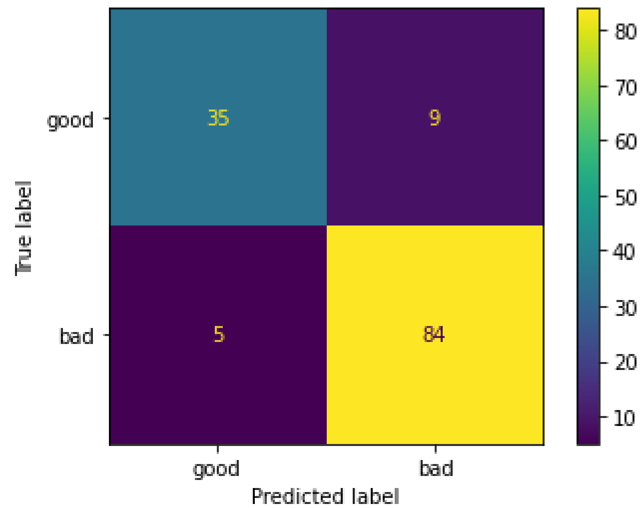
Validation Set Performance

Autoencoder Image Reconstruction





Feed Forward Neural Network Classification



Validation accuracy = 0.8947

Limitations

- The autoencoder was trained on just healthy leaf images so there is no guarantee about a consistent encoding of unhealthy leaves.
- The autoencoder and the feed forward neural network (FFNN) were not being trained simultaneously towards the same task. The FFNN was trying to classify both healthy and unhealthy leaves condensed into the latent space by an autoencoder trained only on healthy leaves. It would have been more efficient to train the autoencoder on both types of leaves.

Alternate Approaches and Methods

1. **Multiclass classification:** We had two different types of diseases in the dataset, but chose to lump them together. Maybe if we attempt to learn the differences between them, we can perform better overall.
2. **Knowledge-based approach**: We can imagine a knowledge base which knows more about the visual features of each type of disease, and a computer vision algorithm that attempts to extract these features.
3. **Data augmentation**: There are several ways to increase the small amount of training data that we have - we can blur, zoom, rotate, and realign the images to create “new” data points.
4. **Better targeting:** We can first try to locate the leaf of interest in the image (by segmentation / bounding boxes, for example), and then apply classification techniques.
5. **Transfer learning:** We can try to use a classifier pretrained on some other (similar) classification task and fine-tune it for our needs.
6. **K-Nearest Neighbors:** KNN performs well on small data sets, but we will need to convert the images to a latent representation (such as with the autoencoder above) before it would make sense to measure “distance” between images.
7. **Denoising Autoencoder:** We can try to mask portions of the leaf in the input, and train the autoencoder. This way, it learns a more robust representation of the leaves and is more resistant to noise.