

Leaf classification

CNN supervised machine learning

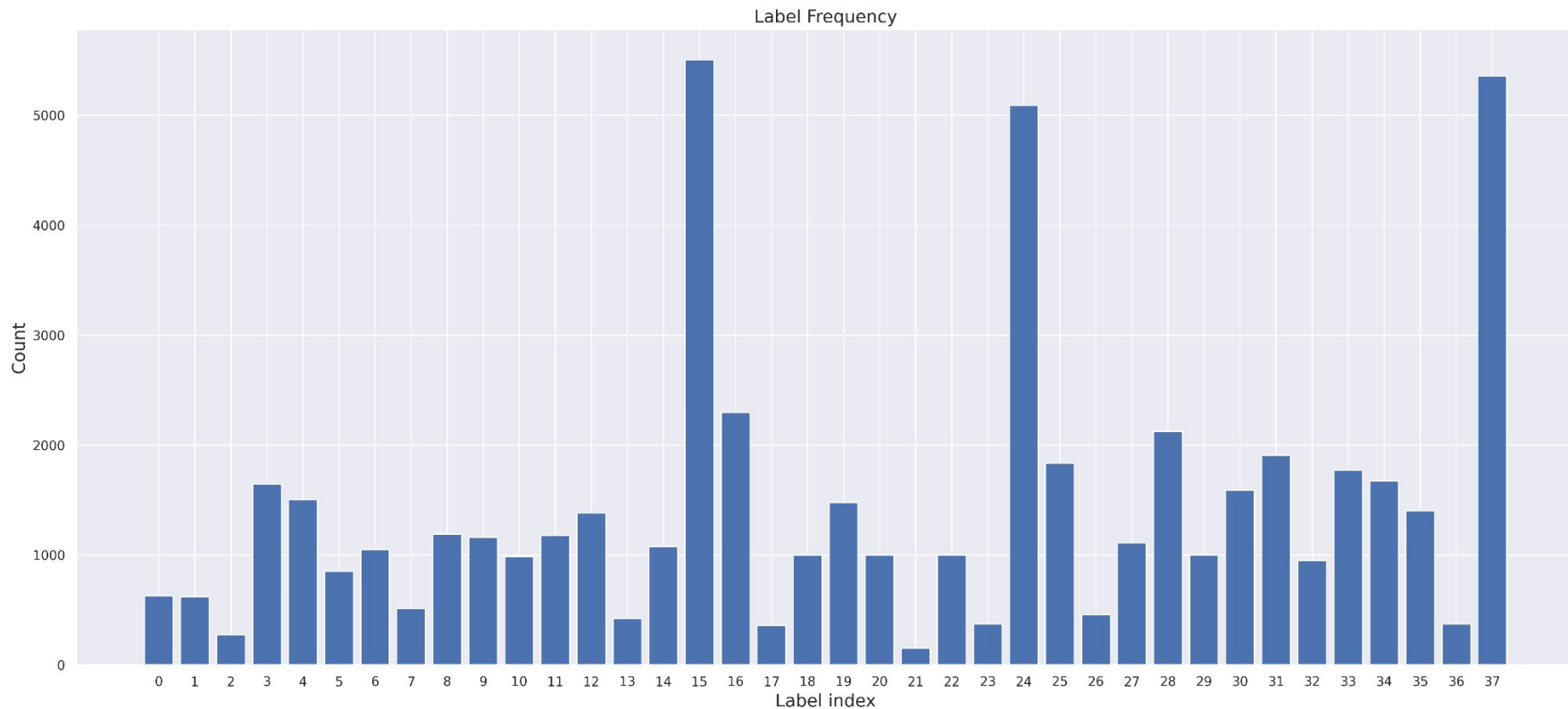
Dataset description

- 54303 images
 - size: 256x256
 - RGB space
 - 13 species
 - 38 categories
 - healthy and unhealthy plant leaves
 - unbalanced categories
- Apple
 - Blueberry
 - Cherry
 - Corn
 - Grape
 - Orange
 - Peach
 - Pepper
 - Potato
 - Raspberry
 - Squash
 - Strawberry
 - Tomato
 - Empty background

Dataset: index of labels

1.Apple scab	11.Corn northern leaf blight	21.Pepper healthy	31.Tomato early blight
2.Apple black rot	12.Corn healthy	22.Potato early blight	32.Tomato healthy
3.Apple cedar apple rust	13.Grape black rot	23.Potato healthy	33.Tomato late blight
4.Apple healthy	14.Grape black measles	24.Potato late blight	34.Tomato leaf mold
5.Background without leaves	15.Grape leaf blight	25.Raspberry healthy	35.Tomato septoria leaf spot
6.Blueberry healthy	16.Grape healthy	26.Soybean healthy	36.Tomato spider mites two-spotted spider mite
7.Cherry powdery mildew	17.Orange haunglongbing	27.Squash powdery mildew	37.Tomato target spot
8.Cherry healthy	18.Peach bacterial spot	28.Strawberry healthy	38.Tomato mosaic virus
9.Corn gray leaf spot	19.Peach healthy	29.Strawberry leaf scorch	39.Tomato yellow leaf curl virus
10.Corn common rust	20.Pepper bacterial spot	30.Tomato bacterial spot	

Dataset distribution



Dataset sample images



Tomato - Target Spot



Orange - Haunglongbing (Citrus greening)



Tomato - Late blight



Potato - Early blight



Apple - healthy



Apple - Cedar apple rust



Pepper, bell - healthy



Tomato - Spider mites Two-spotted spider mite



Tomato - Bacterial spot



Tomato - Late blight



Squash - Powdery mildew



Tomato - healthy



Cherry - Powdery mildew



Tomato - Spider mites Two-spotted spider mite



Tomato - Tomato mosaic virus

Dataset processing

- Split:
 - train 80%
 - validation 15%
 - test 5%
- Random data augmentation:
 - brightness
 - contrast
 - flip
- Class weighting
- Image scaling surprisingly counterproductive! It was not implemented.

Class weighting

$$\text{class weight} = \frac{n_{\text{samples}}}{n_{\text{classes}} \times \text{bincount}(y)}$$

Class unbalance is compensated through a class weight using the values of:

- `n_samples`
- `n_classes`
- `bincount(y)`: a function that counts the number of occurrences of each value in an array `y`
- `y`: the array of the data labels

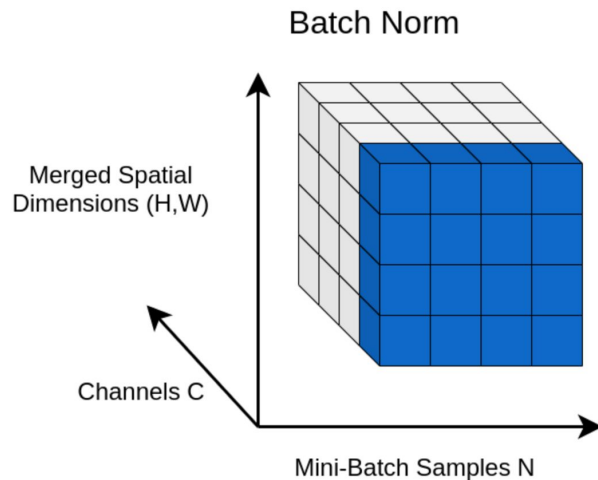
Source: https://scikit-learn.org/stable/modules/generated/sklearn.utils.class_weight.compute_class_weight.html

The model

- Custom architecture composition:
 - Three CNN blocks
 - A classification block
- Loss function: Sparse Categorical Cross-entropy, *because data is discrete multiclass*
- Optimizer: Adam, *computationally efficient, has little memory requirement, invariant to diagonal rescaling of gradients, and is well suited for problems that are large in terms of data/parameters*

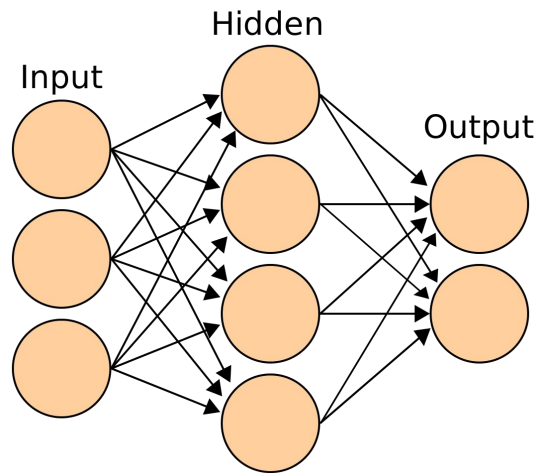
CNN block

- 2D convolutional layer
- respectively 16, 32 and 64 filters per block
- Kernel size: 3
- ReLU activation
- L2 kernel regularizer
- stride equal to 2 for image size reduction
- Batch Normalization
- Dropout with probability 0.25 to handle overfitting



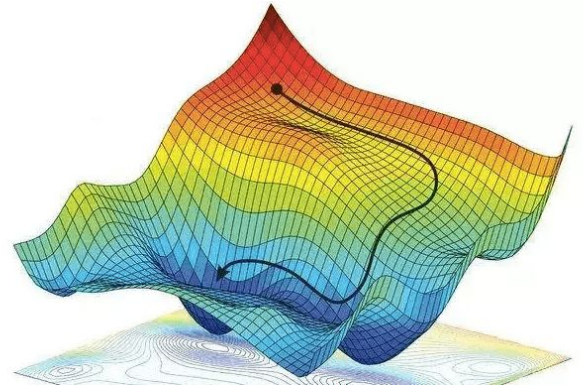
Classification block

- Composition: two feedforward, fully connected MLP
- Dimensions: 64 and 38 (as number of categories)
- Dropout with probability 0.5



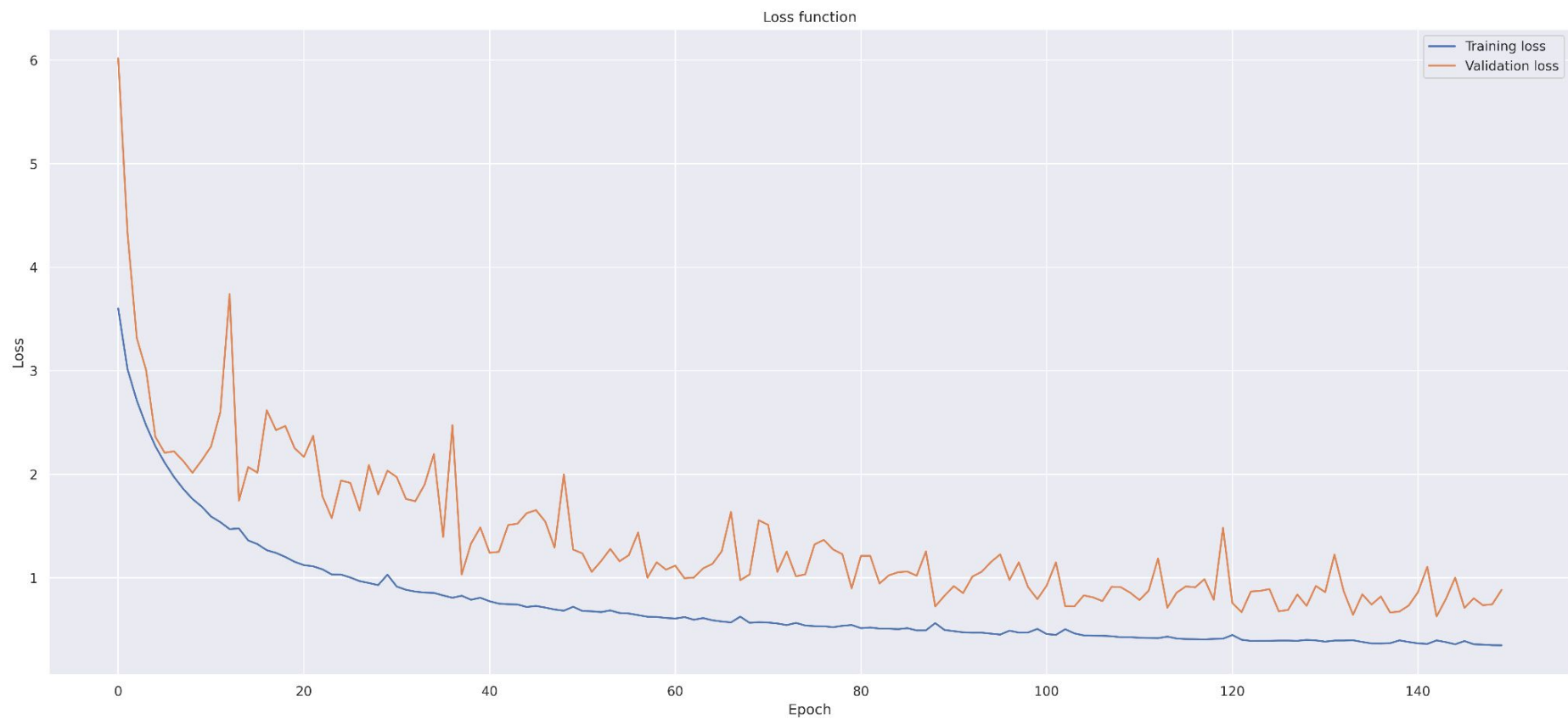
The optimizer: Adam

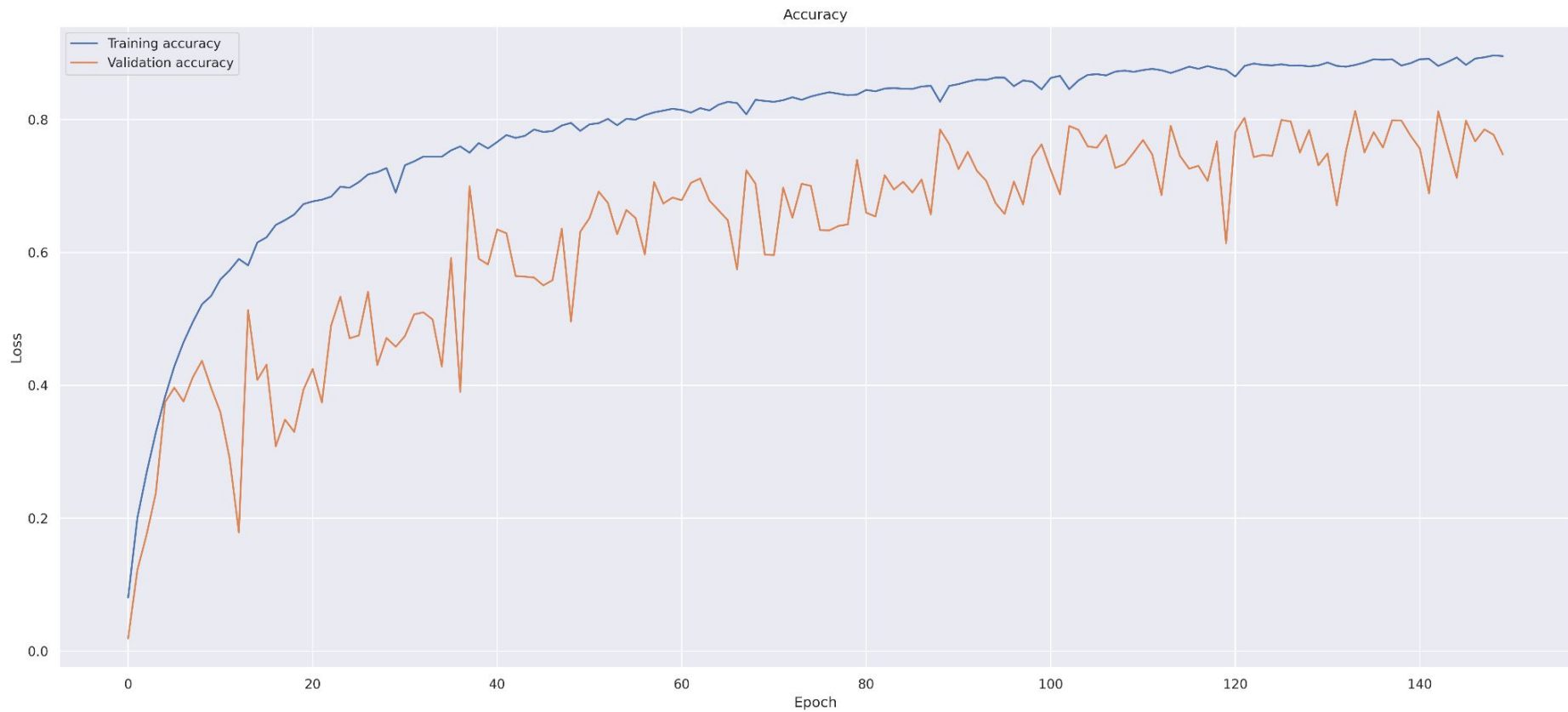
- stands for: adaptive moment estimation
- basically an extended version of stochastic gradient descent
- learning rate: $10e-4$
- $\text{decay} = \text{learning rate} / \text{number of epochs}$



Model training

- Trained for 150 epochs
- 30,662 number of parameters
- Metric: Sparse Categorical Accuracy
- Hardware: Intel Xeon CPU @2.20 GHz, 13 GB RAM, Tesla P100 accelerator, and 12 GB GDDR5 VRAM
- Training time is circa one hour, with 20 seconds circa for each epoch
- Test performance: loss: 0.8939 - sparse categorical accuracy: 0.793





References

- [Dataset source](#)
- [Machine learning software library](#)
- [Jupyter notebook of the project](#)