CNN-Based Rotation Correction

Advanced Machine Learning
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Introduction

Quarter-Turn Rotations

- Hand-crafted CNN
- Feature extraction
- Fine-tuning

Full-Range Rotations

- Applying the best method of the first part

Dataset Preparation

- **Dataset** created by manually sampling from:
  - Landscape Pictures [1] --> 110 images
  - Unpaired Day and Night cityview images [2] --> 190 images

- 60-20-20 Train/Val/Test split
- Each image is then **divided** into one or multiple squares
- Dataset becomes only square images, with different resolutions
- 359 train, 166 val, 117 test.
- Random rotations are applied while training, through a data loader

Figure 1: Image 1

Figure 2: Split Image 1

Figure 3: Image 2

Figure 4: Split Image 2

[1] https://www.kaggle.com/datasets/arnaud58/landscape-pictures
[2] https://www.kaggle.com/datasets/heonh0/daynight-cityview

Hand-Crafted CNN Approach

Hand-Crafted CNN Approach

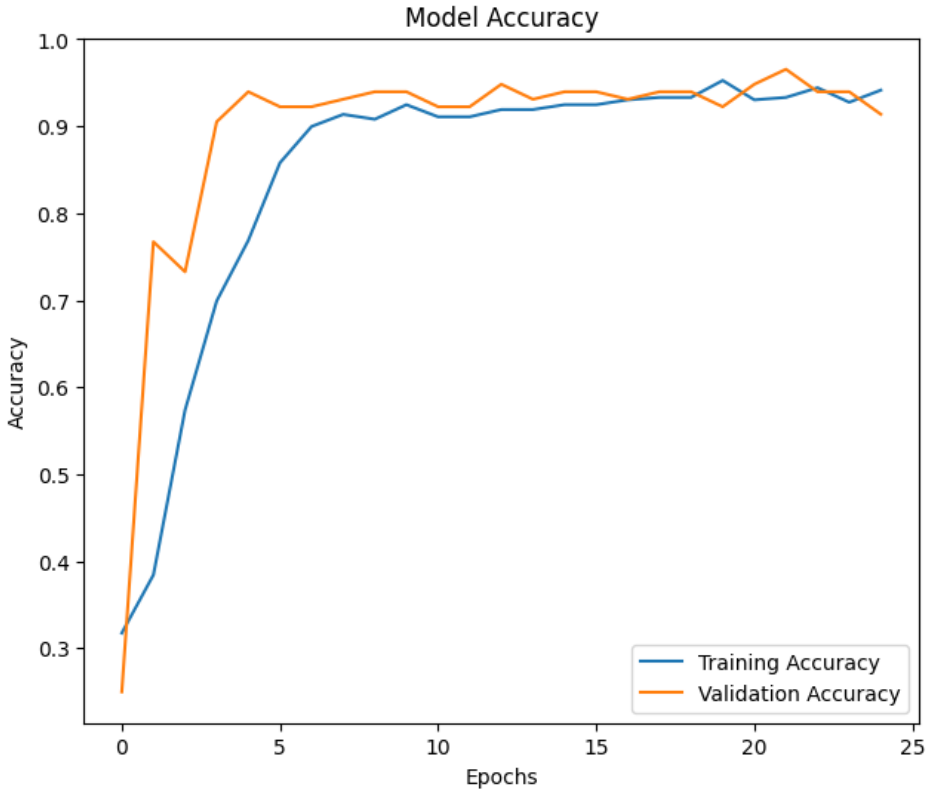
- Creating and training a **CNN from scratch**

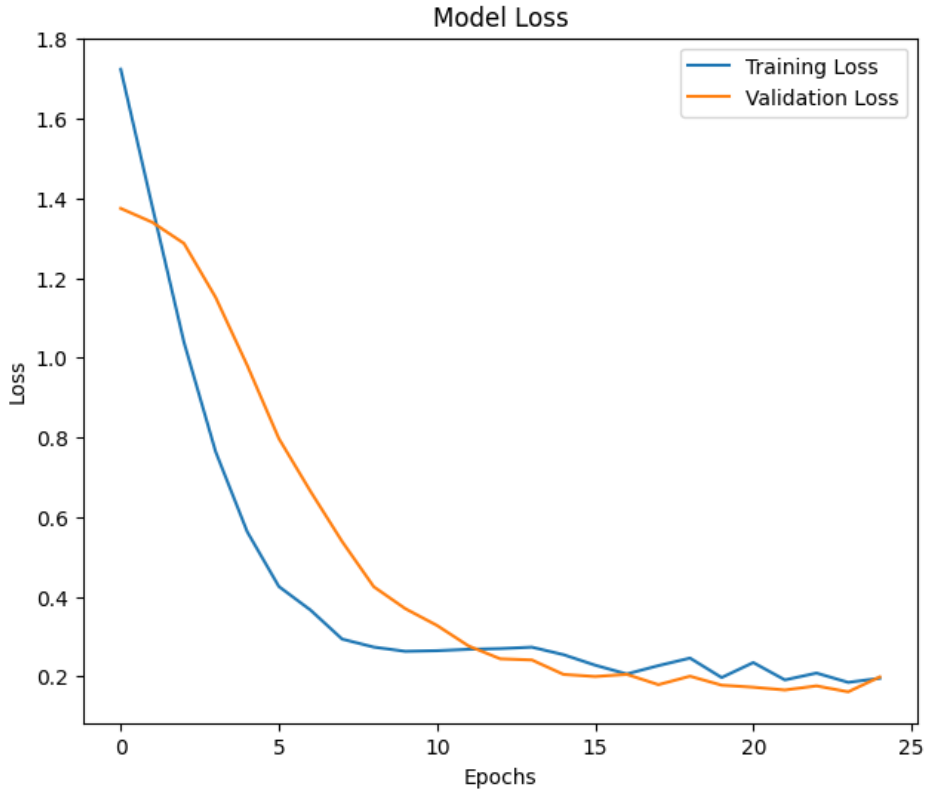
Layer Type	Output Shape	Param #
Input	(224, 224, 3)	/
Conv, 16, 3x3	(111, 111, 16)	448
Batch Normalization	(111, 111, 16)	64
Conv, 32, 3x3	(55, 55, 32)	4’640
Batch Normalization	(55, 55, 32)	128
Conv, 64, 3x3	(27, 27, 64)	18’496
Batch Normalization	(27, 27, 64)	256
Conv, 128, 3x3 + Dropout 40%	(13, 13, 128)	73’856
Conv, 128, 3x3 + Dropout 50%	(6, 6, 128)	147’584
Flatten	(4608)	0
Dense, 128 + Dropout 50%	(128)	589,952
Output	(4)	516

- Total trainable parameters: 835,716
- **Data loader** that rotates input images randomly (0°, 90°, 180° 270°)

Hand-Crafted CNN: Evaluation

- The model **converges** rapidly

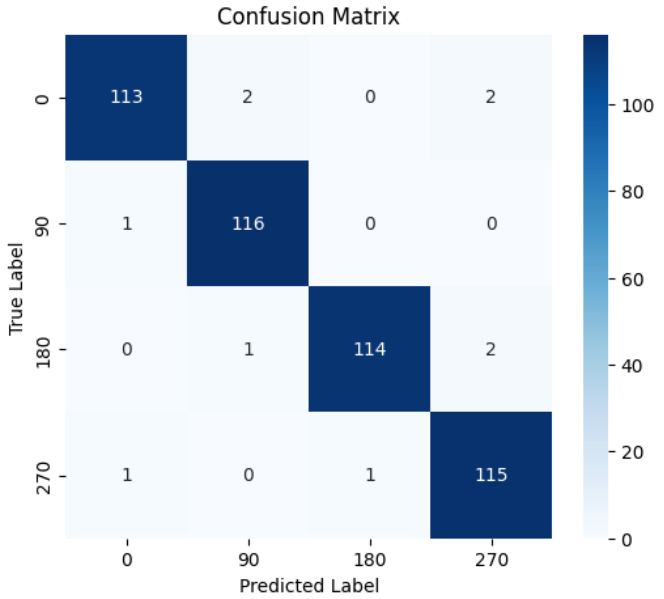




Hand-Crafted CNN: Evaluation

- **Test set** created by rotating the test images by every possible quarter-rotation
- **Classification report:**

	Precision	Recall	F1-Score	Support
0	0.98	0.97	0.97	117
90	0.97	0.99	0.98	117
180	0.99	0.97	0.98	117
270	0.97	0.98	0.97	117
Accuracy			**0.98**	468
Macro avg	0.98	0.98	0.98	468
Weighted avg	0.98	0.98	0.98	468



- **Great performance**: 98% accuracy
- Very **few misclassifications**, we can retrieve and plot them to further analyze the model

Hand-Crafted CNN: Evaluation

- **Misclassified images:**

- **Repeated mistakes** on the same test images
  - Indicates a **lack of generalization** in the model, due to the small dataset's size

Features Extraction Approach

Feature Extraction Approach

- **Feature extraction** from MobileNetV2
- Feature arrays used on a **SVM Classifier**
- Could be a good approach considering the **small dataset's size**

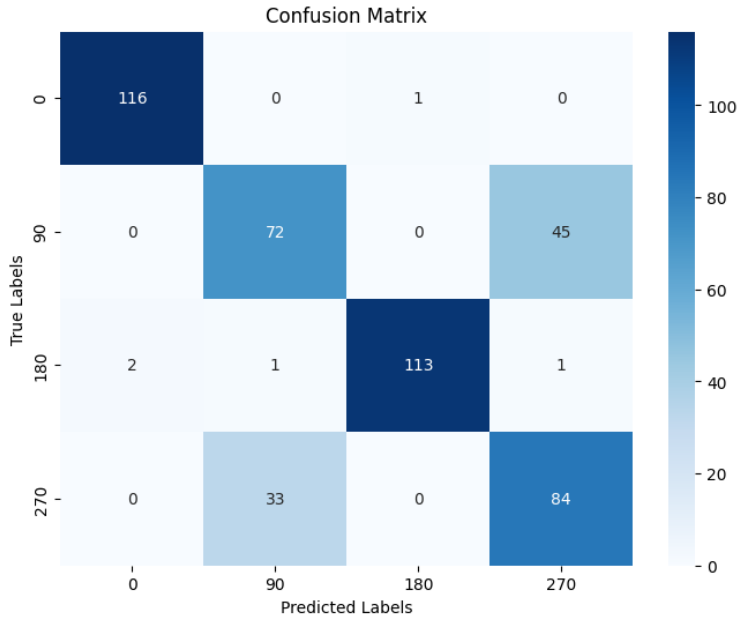
- Images **rotated by every possible rotation** (0°, 90°, 180° 270°) to give it the best chance of success (for all train, val and test images)
  - The function made can be set to fewer unique rotations, by changing a parameter

- SVM fitted and hyperparameter optimization done, using the validation set

Feature Extraction: Evaluation

- Used the best parameters on a new SVM, fitted with both train and validation data, to attempt to increase the performance
  - The performance increase was very **minor**

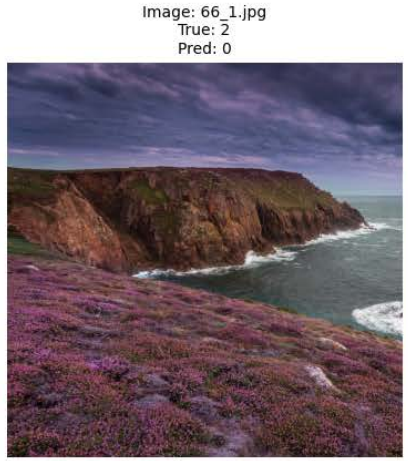
Class	SVM Best Parameters			SVM with Added Val Data		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
0	0.98	0.98	0.98	0.98	0.99	0.99
1	0.64	0.60	0.62	0.68	0.62	0.65
2	0.98	0.97	0.98	0.99	0.97	0.98
3	0.63	0.68	0.65	0.65	0.72	0.68
Accuracy			**0.81**			**0.82**
Macro Avg	0.81	0.81	0.81	0.82	0.82	0.82
Weighted Avg	0.81	0.81	0.81	0.82	0.82	0.82

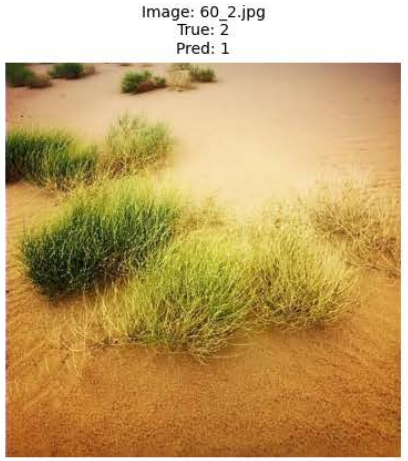


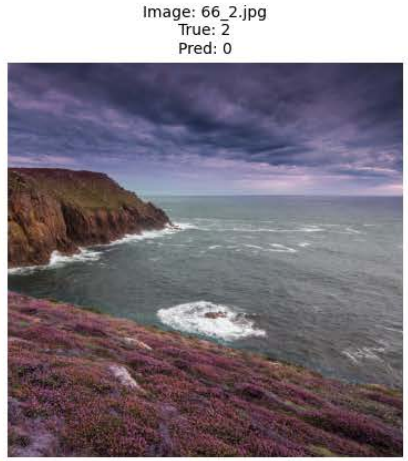
- **0° and 180°**'s performances are comparable to the previous method
- **90° and 270°** are greatly **confused with each other**
- Most likely it's due to a **lack of information** about these type of rotations in the extracted features

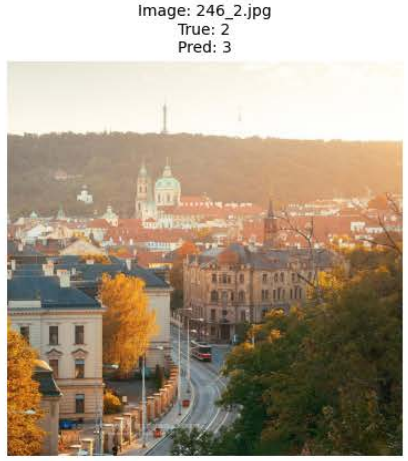
Feature Extraction: Evaluation

- Plotting all the **mistakes** made on **0° and 180°** classes:
  - (images not rotated)







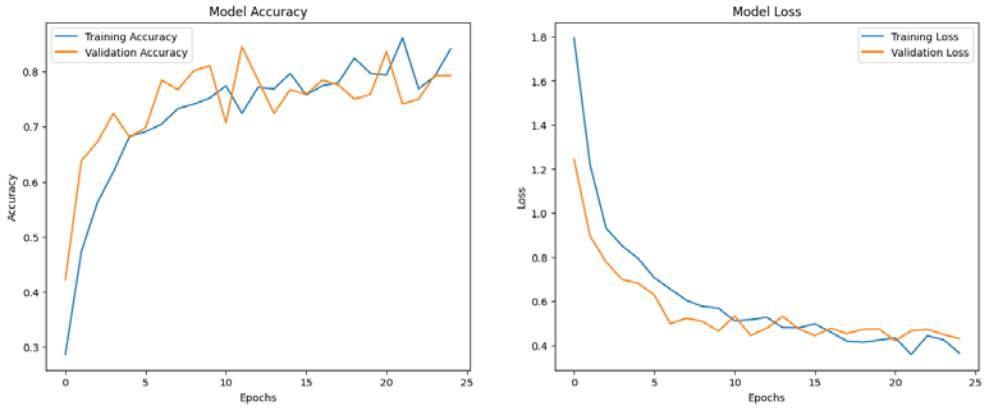


- Two images are misclassified for both rotations
  - **Different** from the images of the previous method
  - **This cannot be a sure indication of possible better generalization**

Fine-Tuning Approach

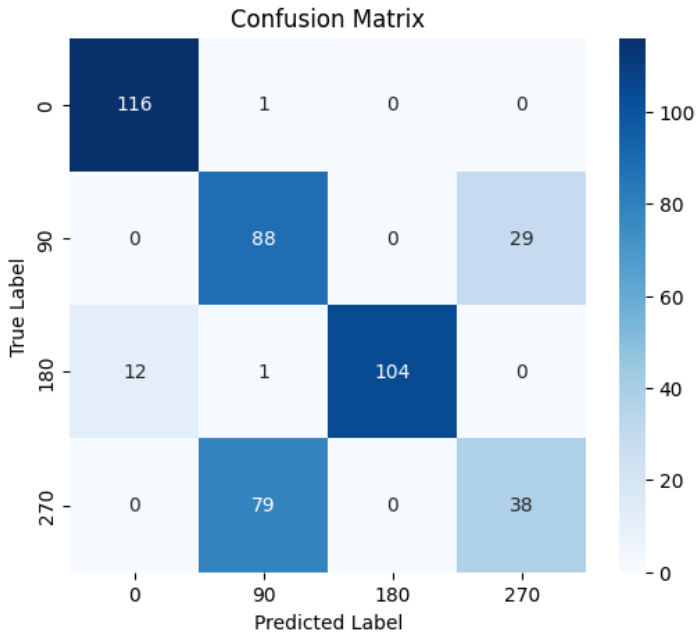
Fine-Tuned CNN: Evaluation

- **Fine-tuning** of MobileNetV2 pre-trained on ImageNet
  - **Freezing** the base model's weights at the start
  - Adding a **dense layer** (512) with 0.6 dropout and the output layer
  - Using MobileNetV2's preprocessing pipeline to prepare the images



	Precision	Recall	F1-Score	Support
0	0.91	0.99	0.95	117
90	0.52	0.75	0.62	117
180	1	0.89	0.94	117
270	0.57	0.32	0.41	117
Accuracy			**0.74**	468
Macro avg	0.75	0.74	0.73	468
Weighted avg	0.75	0.74	0.73	468

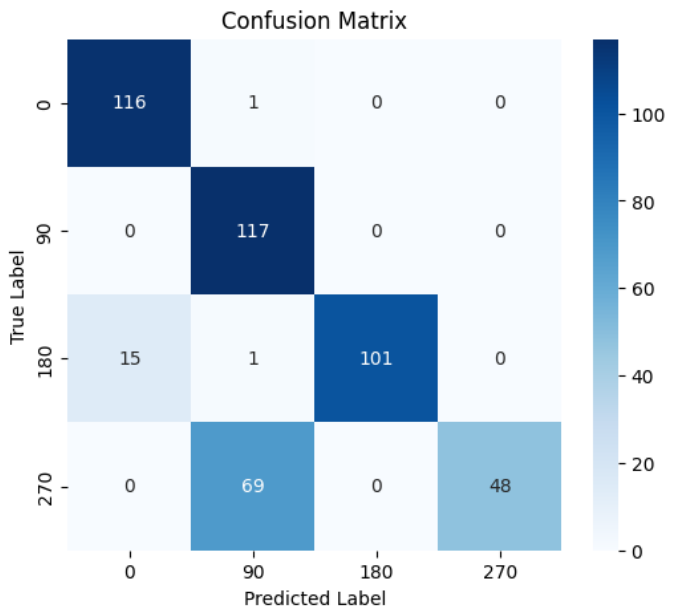
- Seems to be suffering from the **same issue** as the feature extraction method
- The **issue** stands in the **pre-trained network**



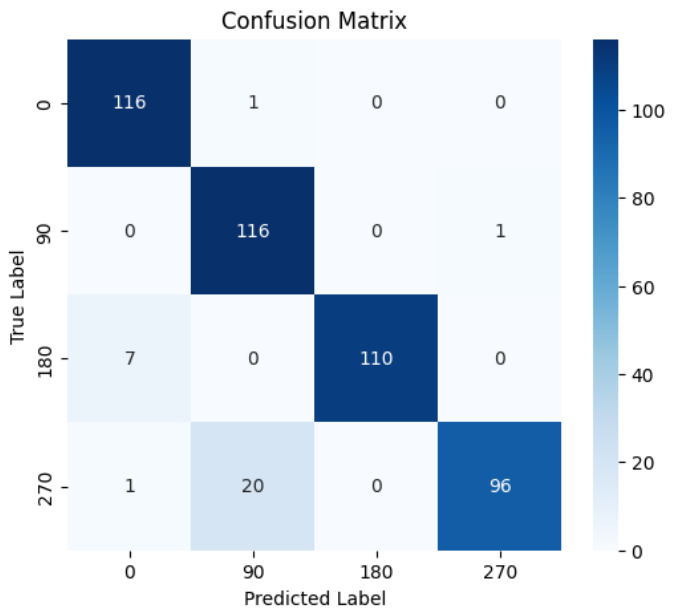
Further Fine-Tuning (unfrozen)

- **Further fine-tuning** un-freezing the base model's weights, with a lower learning rate

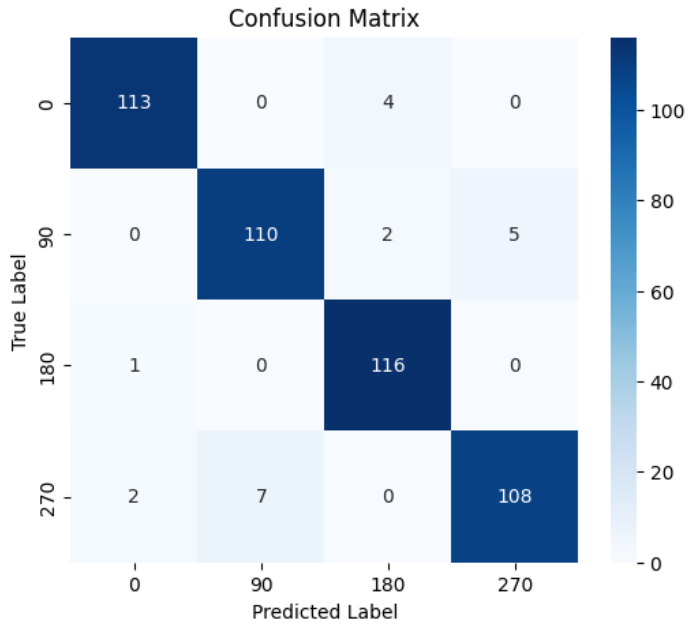
Model 2 accuracy: 82%



Model 3 accuracy: 94%



Model 4 accuracy: 96%



- **Increasingly more training** on the previous model
- The issue on the **classes 90° and 270°** slowly gets «fixed»
  - Not reaching the hand-crafted performance (could be fine-tuned more though)
- The classification task for which MobileNetV2 was trained is **not compatible with this task**, as it does not capture **lateral-rotation information** well

Full Range Rotations

Full Range Rotations

- Expanding the previous methods, while applying the best one (**hand crafted CNN**) to this task
- Images can now be **rotated any amount** from 0° to 360°.
- Customs functions were necessary to rotate the images
  - **Black fill** must be deleted, otherwise the model would use it to learn
  - The **biggest square** that fits inside the rotated image is cropped [2]

[2] https://math.stackexchange.com/questions/828878/calculate-dimensions-of-square-inside-a-rotated-square

Full Range Rotations

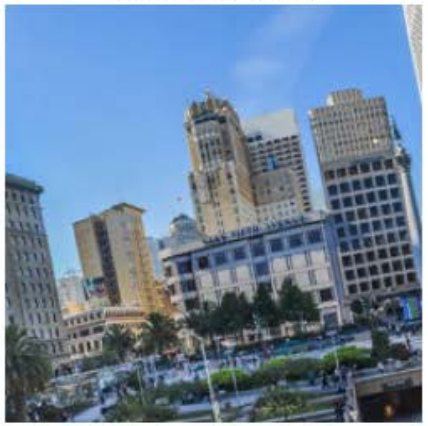
- The **output** cannot be one-hot encoded anymore, but it also shouldn't be the rotation amount in degrees.
  - If the rotation amount was used, rotations like **1°** and **359°** would be seen as **polar opposites**, not close rotations.

- The rotations were converted to two ***x* and *y* values**:

$$x = \cos(\theta) \qquad y = \sin(\theta)$$

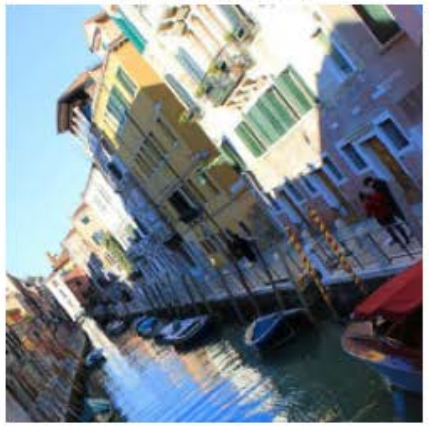
  - where θ is the rotation angle in radians.

348.41°
(x: 0.98, y: -0.20)



128.90°
(x: -0.63, y: 0.78)

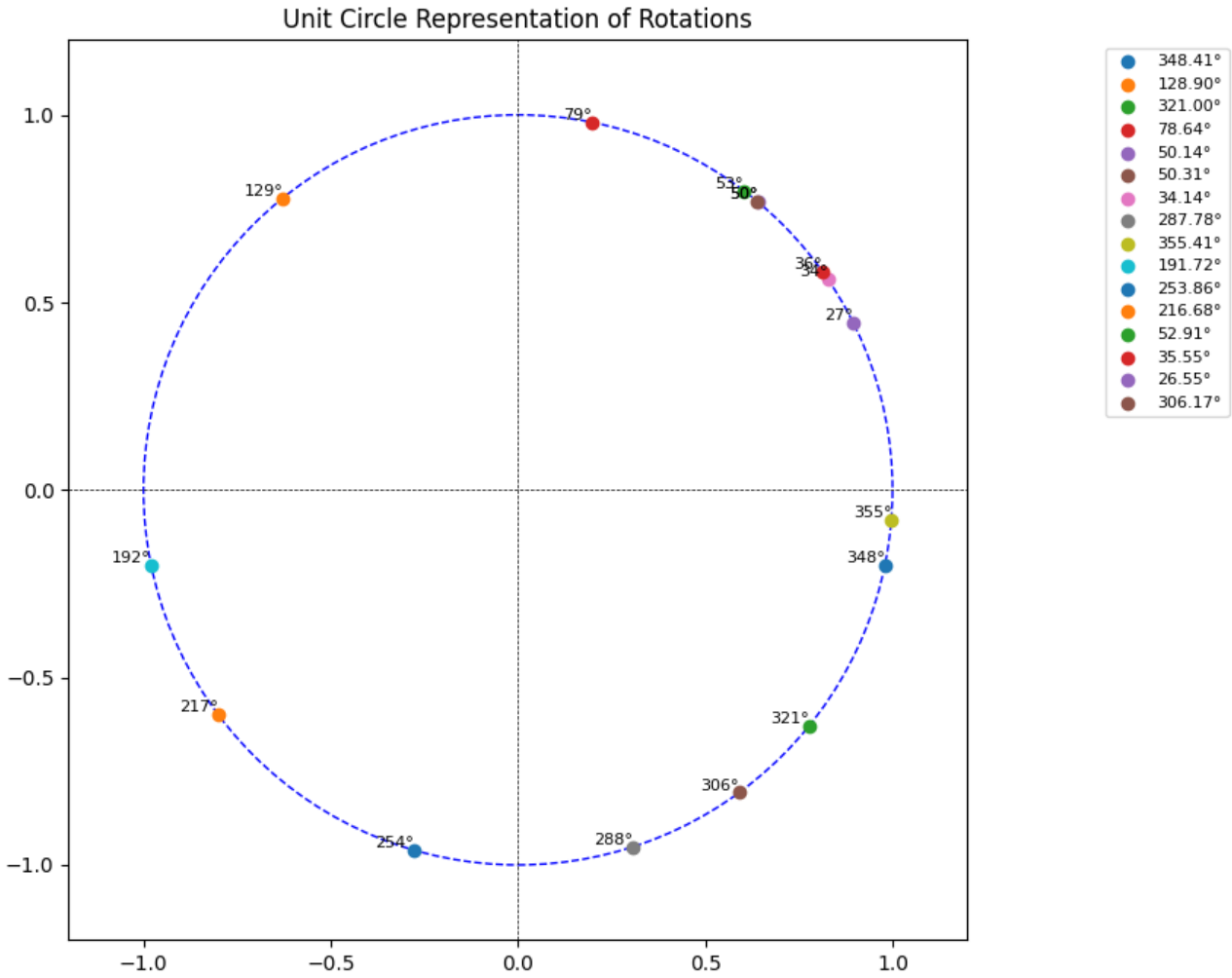
321.00°
(x: 0.78, y: -0.63)



78.64°
(x: 0.20, y: 0.98)

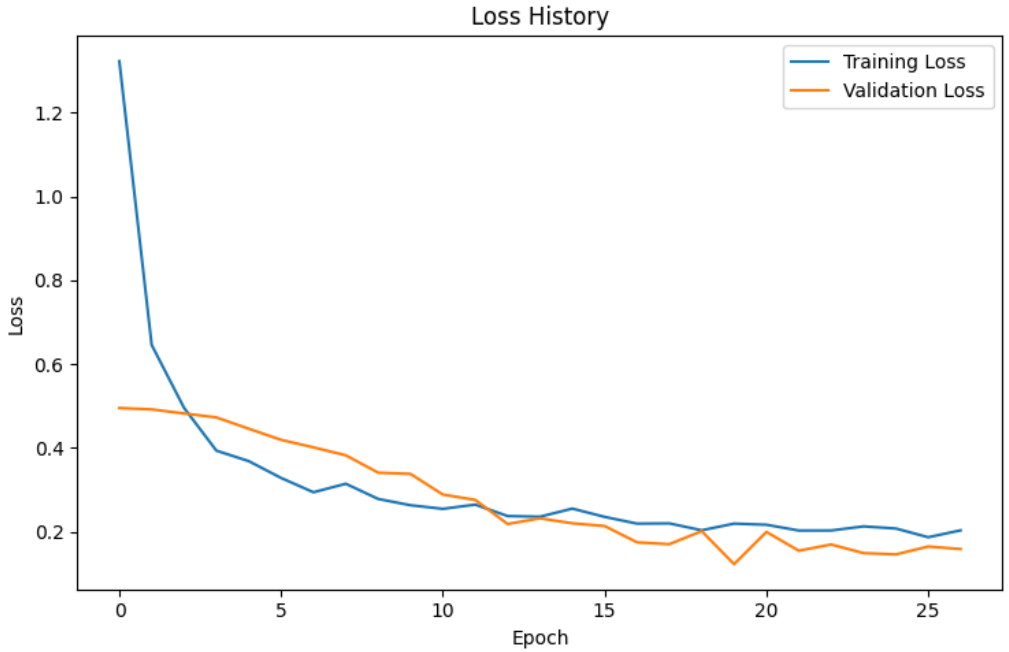
Full Range Rotations

- Rotations like 0° and 259° are **next to each other**
- Rotations like 0° and 180° are **opposite of each other**



Full Range Rotations: Evaluation

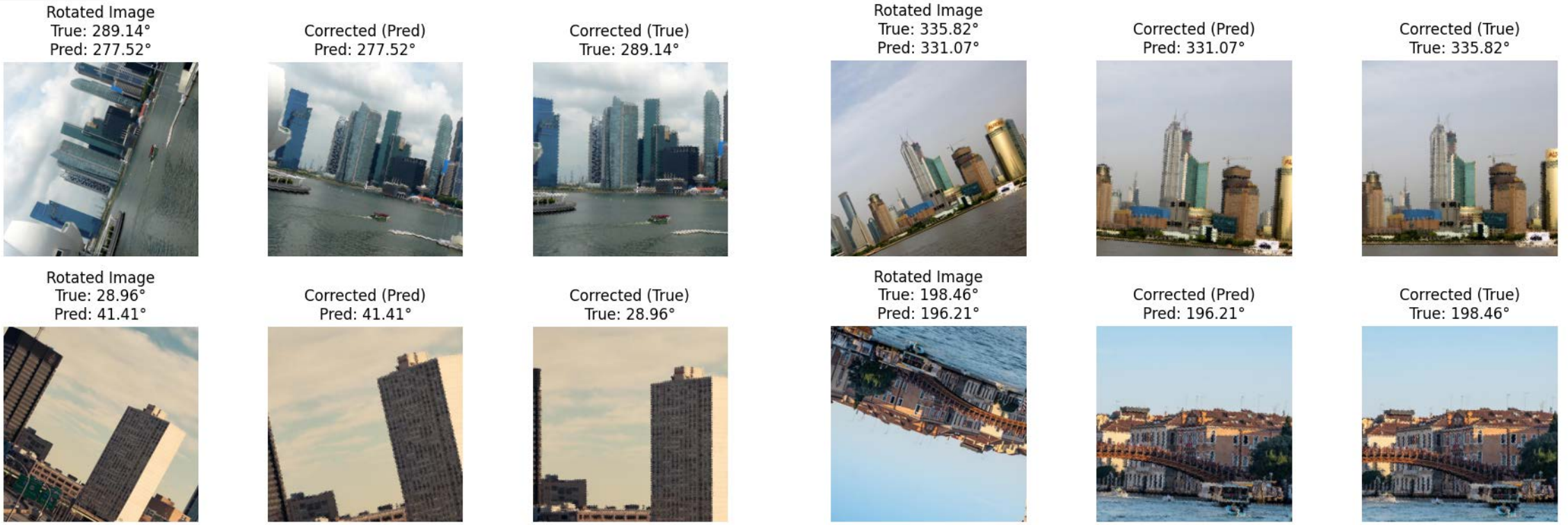
- The **same hand-made model architecture** was used
  - With slightly higher learning rate



- Test Loss (mse): 0.15
- **Average error in degrees**: 27.08°
  - Fairly **acceptable** considering that the images in the dataset are **not necessarely perfectly level**. A more curated dataset could improve the performance.
  - The model's **architecture could be improved**, for example with a bigger dense layer before the output, 128 neurons might be too little

Full Range Rotations: Evaluation

- To better evaluate the results, let's **correct the rotations**:



- **Small rotation errors** are very noticeable to the human eye

Thanks for your attention

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