

Improving Breast Mass Classification using Control-Driven Data Augmentation

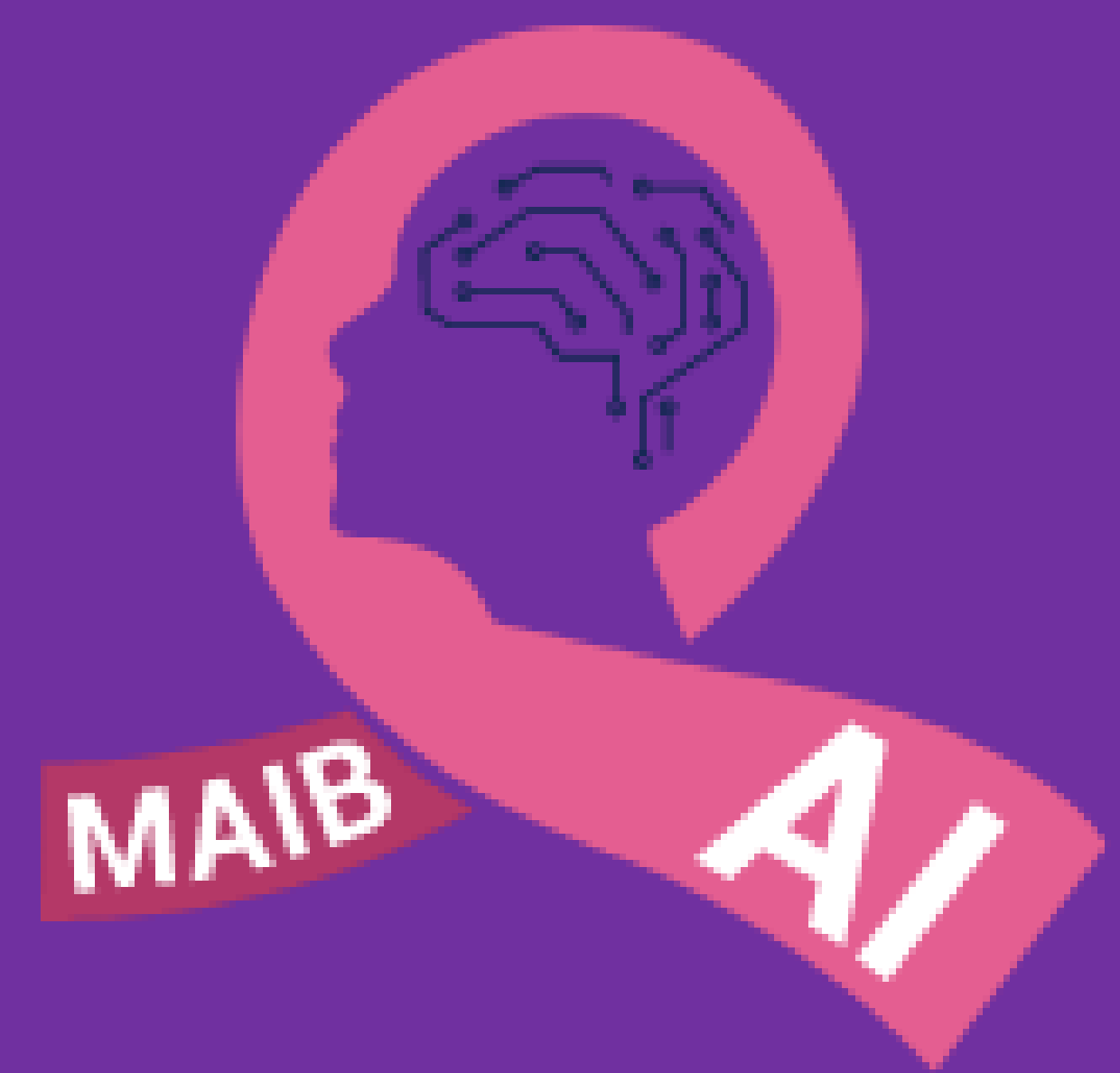
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INTRODUCTION

Overall vision:

To develop a breast-mass AI inspector that provides radiologists with relevant information when they select or outline a breast mass on a mammographic image.

Dataset and classification task:

Our dataset is formed by mammographic images selected from the OPTIMAM imaging database (OMBI-DB) (for access see [1] and for database description see [2]). A subset of images in OMI-DB contains professionally marked lesions, with bounding box coordinates, providing a ground-truth labelled dataset.

As an initial task, we investigate the ternary classification of breast masses into the three categories:

- well-defined masses (class 0)
- ill-defined masses (class 1)
- spiculated masses (class 2)

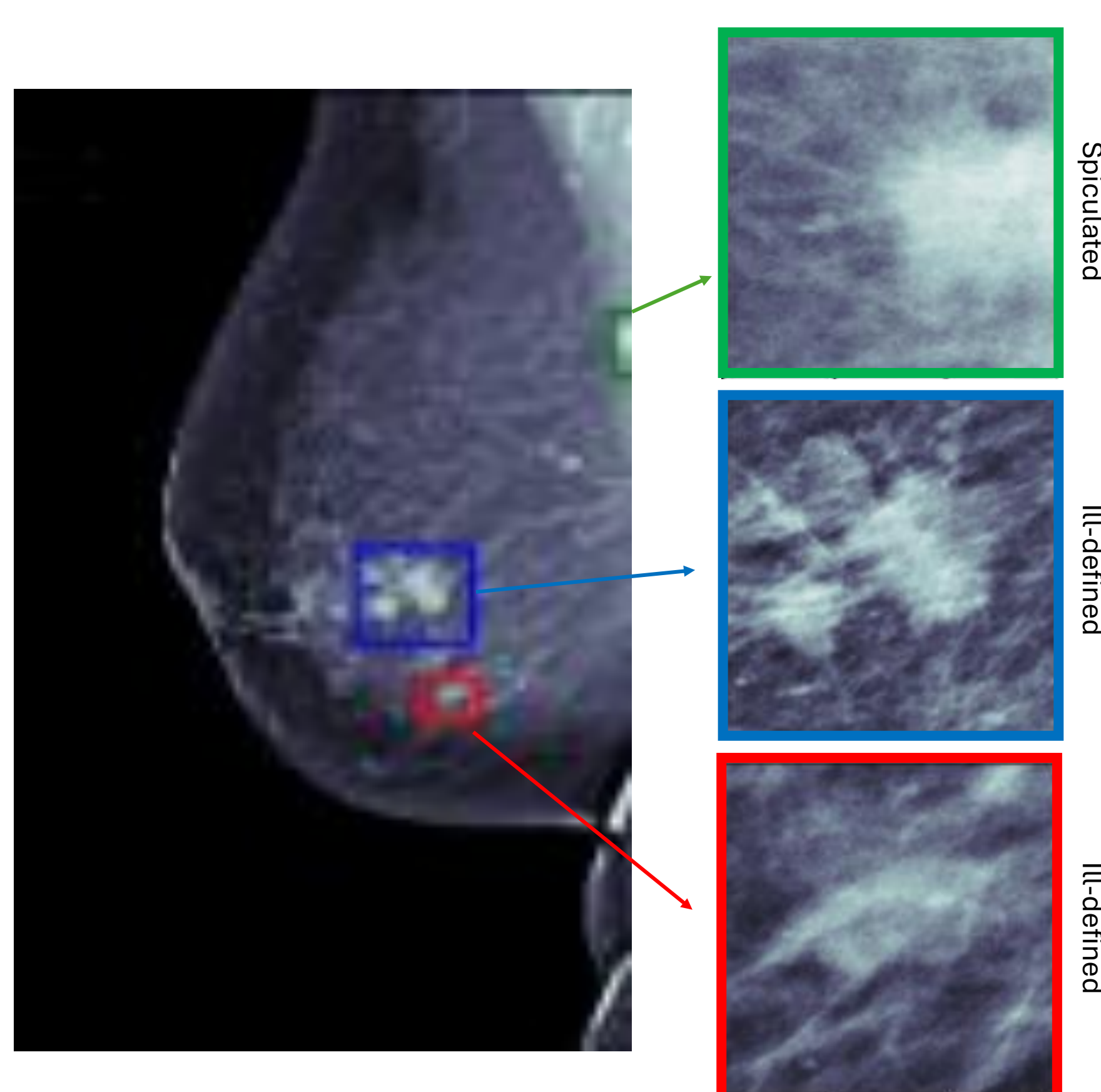


Figure 1. Visualization of patch extraction of mass lesions from full mammogram image.

REFERENCES

1. <https://medphys.royalsurrey.nhs.uk/omidb/>
2. M. D. Halling-Brown et al., "OPTIMAM Mammography Image Database: A Large-Scale Resource of Mammography Images and Clinical Data," Radiol. Artif. Intell. E200103 (2020).
3. J. B. Christensen et al., "Ctrl-A: Control-Driven Online Data Augmentation," arXiv:2603.21819 (2026).

METHODOLOGY

Image patches are reshaped into square patches by extending the shorter dimension and subsequently resizing to images of 200 by 200 pixels (see Fig. 1). In total: 3761 mass-containing patches are curated; with class counts of 544 (0), 1730 (1), and 1487 (2).

We employ a ResNet-22 conv-net model with ~11.5M trainable parameters and use a random 80/10/10 train/validation/test split. Models are trained for 150 epochs using a cosine-annealed learning rate schedule.

Data-augmentation development:

Data augmentation (DA) provides a proven means for enhancing model performance and generalisability in situations with scarce data availability (see Fig. 2 for DA examples).

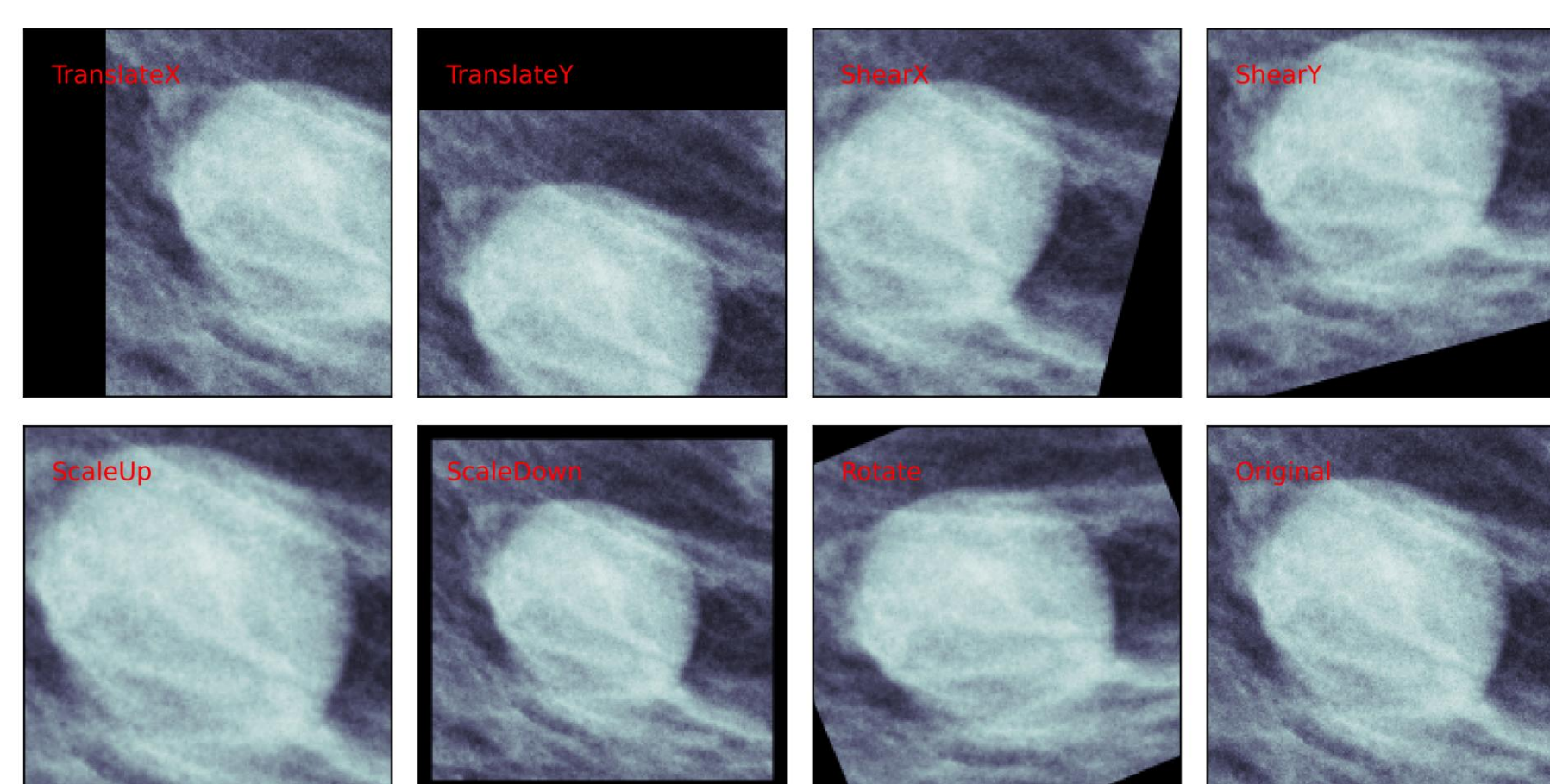


Figure 2. Operations applied with moderate magnitude.

However, it remains a challenge to determine relevant augmentation magnitudes for the different operations applied to images on the fly. This is addressed by ControlAugment (Ctrl-A) [3], which uses control theory to dynamically balance the training-validation-loss ratio by sequentially updating the DA magnitudes to realise adaptive regularisation. The procedure for determining the maximum augmentation magnitude, Γ , for an operation is visualised in Fig. 3.

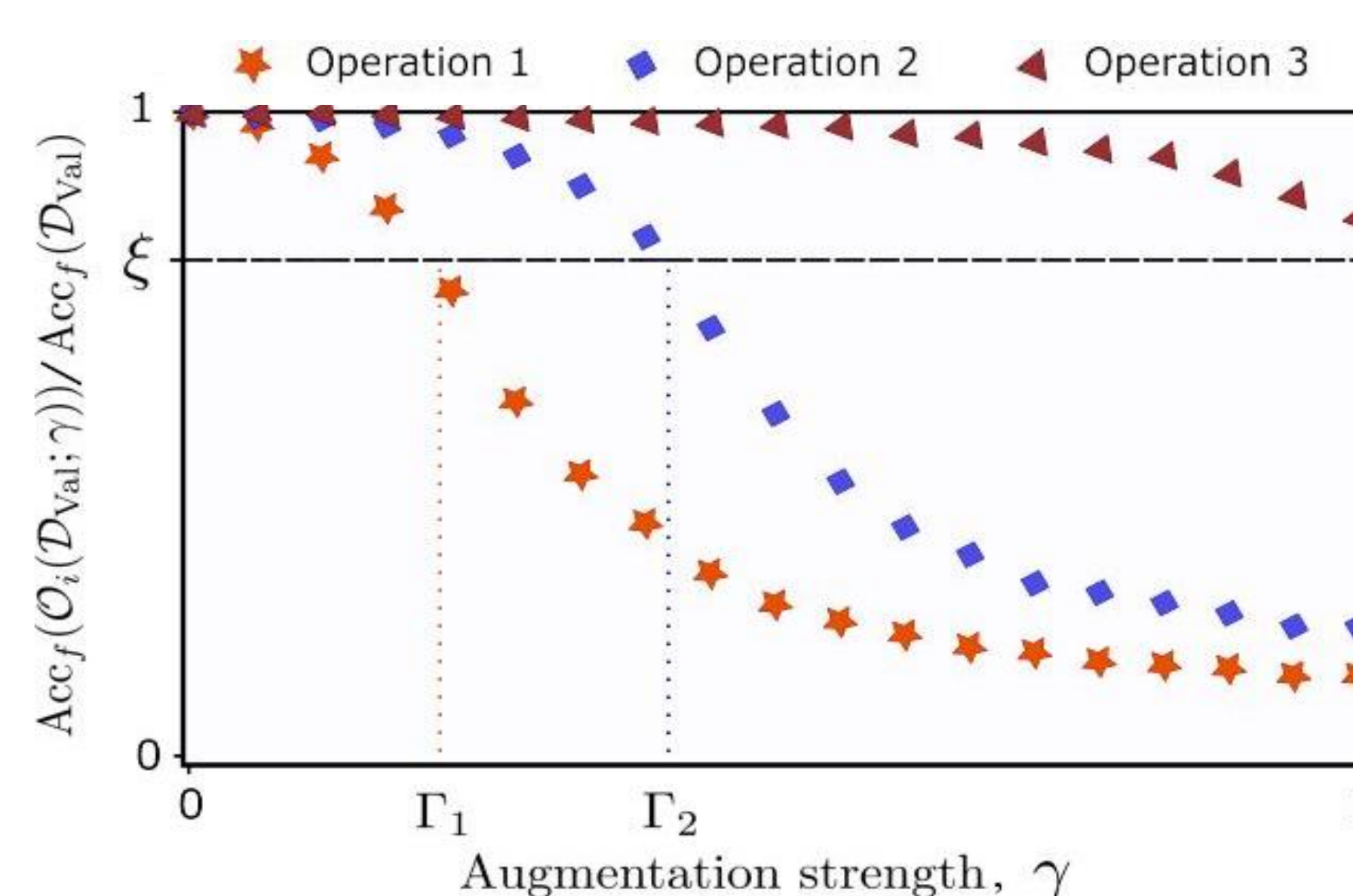


Figure 3. Exemplified relative operation response curves.

RESULTS

Classification results are summarized in Figures 4 and 5 and in Table 1. Figure 4 demonstrates the adaptable regularization enabled by Ctrl-A and the confusion matrix in Fig. 5 illustrates how virtually all misclassification are caused by overlap with the intermediate "ill-defined" class.

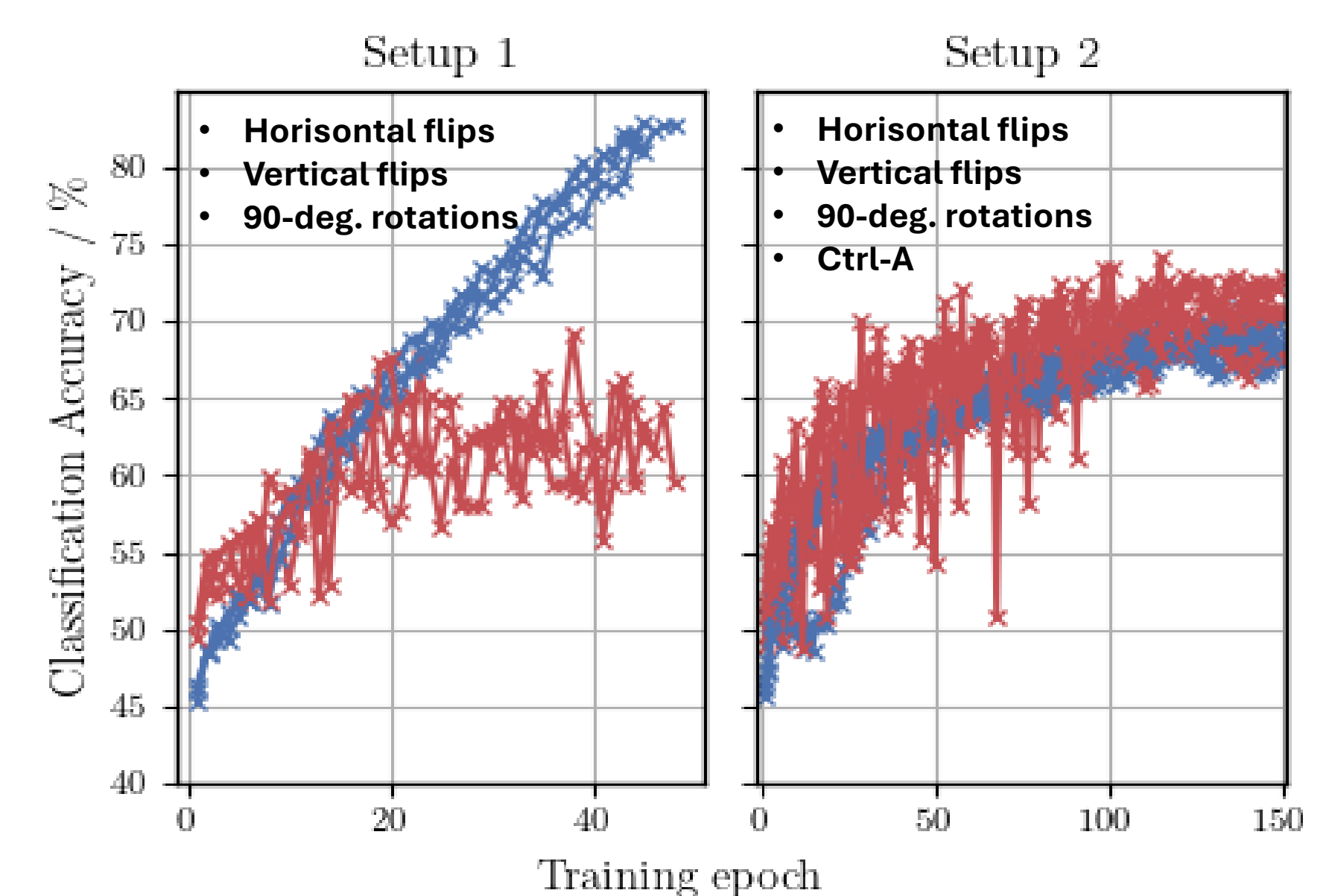


Figure 4. Training-dynamic comparison for the two setups. Blue: Training accuracy; Red: Validation accuracy.

Table 1. Test-set performance (classification accuracy) over 5 model runs using both Setup #1 & #2. TTA: Test-time augmentation (8-fold).

Setup #	Test acc. / %	Test acc. w. TTA / %
1	60.5 $\pm$ 1.0	64.6 $\pm$ 3.6
2	70.9 $\pm$ 1.3	71.5 $\pm$ 0.9

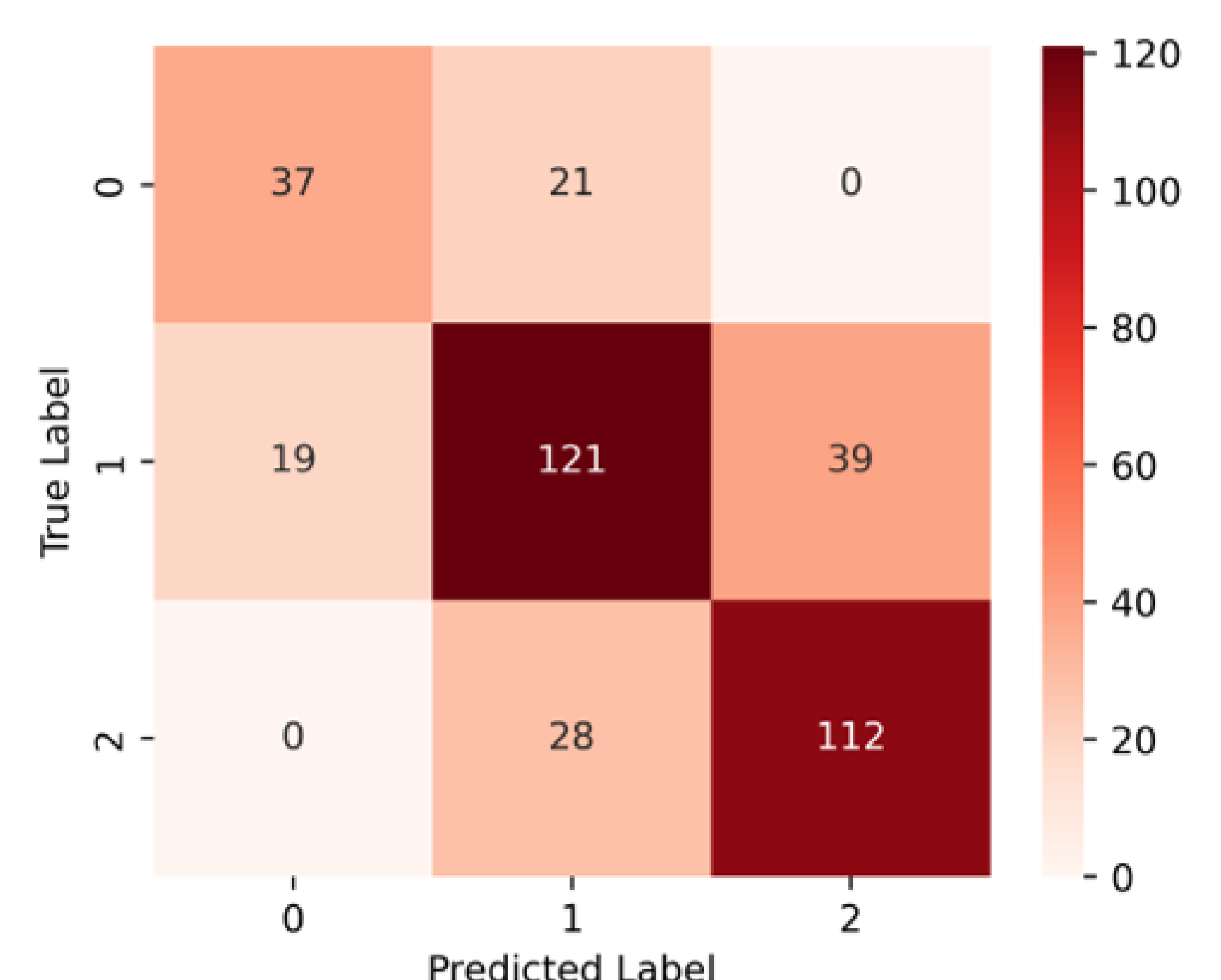


Figure 5. Confusion matrix for test-set predictions after a model run using Setup #2 (w. Ctrl-A).

CONCLUSION

We have demonstrated the potential of machine-learning-based computer vision, coupled with control-driven data augmentation, for classifying breast mass types in mammographic images.