



Weekly Meeting with Dr. Hannah

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The devil is in the detail

1. Cohort Split vs. 5-Fold Stratified Cross-Validation

In this reproducibility study of the CNN-based prognosis model, we followed both evaluation strategies as outlined in the original paper, using the **Canada** and **MAASTRO** datasets.

Cohort Split (CI 95%):

- Training Set → HGJ and CHUS
- Validation Set → HMR and CHUM
- Test Set → Entire MAASTRO dataset (maastro_c/ folder)

▼ 5-Fold Stratified Cross-Validation:

We also performed **5-fold stratified cross-validation** using the **Canada** dataset to ensure class balance (event vs. non-event) across folds.

2. Early Stopping Epoch vs. Best Epoch Performance

- The training pipeline uses an early stopping mechanism, which halts training when the training AUC reaches a defined threshold (e.g., 0.95).
- However, this "does not guarantee the best validation or testing AUC is achieved at that specified epoch". For example:
- Therefore, it's important to review AUCs across all epochs to identify the model's best generalization point.

What Actually Triggers Model Saving?

```
if store_model.get(MODEL_PATH) and \
metrics[VALIDATION][ROC][AUC] > best_val_auc and \
metrics[VALIDATION][ROC][AUC] > store_model.get(THRESHOLD, 0) and \
abs(metrics[VALIDATION][ROC][AUC] - metrics[TRAIN_METRICS][ROC][AUC]) < store_model.get(MAX_DIFFERENCE, 1):
```

This means the model will be saved **only if all of these conditions are met**:

- A valid path is given to save the model (MODEL_PATH)
- Validation ROC AUC is higher than any previous epoch
- The new validation AUC is **above a threshold** (usually 0 if not explicitly set)
- ▼ The difference between training AUC and validation AUC is not too large (typically < 1)

What Happens When a Model is Saved?

```
save_model(
    store_model[MODEL_PATH],
    epoch,
    model,
    optimizer,
    metrics[TRAIN_METRICS][LOSS],
    model_id=store_model[MODEL_ID] or str(type(model))
)
best_val_auc = metrics[VALIDATION][ROC][AUC]
```

This will:

- Save the model to disk using the epoch number in the filename (e.g., model_dm_947.pth.tar)
- Update the best_val_auc

So the "last model saved" is the one that had the best validation AUC during the run.

3. Log Files for AUC Tracking

All results for each outcome have been saved under the log/directory for transparency and further analysis:

```
log_dm.txt
log_lrf.txt
log_os.txt
log_dm_5-fold_cv_fold {0,1,2,3,4}.txt
log_lrf_5-fold_cv_fold {0,1,2,3,4}.txt
log_os_5-fold_cv_fold {0,1,2,3,4}.txt
log_os_5-fold_cv_fold {0,1,2,3,4}.txt
```

Each file contains AUC values for training, validation, and testing across all epochs, which allowed me to identify the true performance peaks.

Table 1: Comparative performance (AUCs) for different outcomes of the reproduced HNC-CNN studies and our result

Event	Paper Result		Our Result		Our Result with our Dataset	
	Cohort split (Cl 95%)	5-fold CV	Cohort split (Cl 95%)	5-fold CV	Cohort split (Cl 95%)	5-fold CV
Distant Metastasis (2 yea	rs)					
Training	0.91 [0.84, 0.96]	0.87 (0.84–0.92)	0.81	0.87	-	-
Validation	0.89 [0.81, 0.96]	0.86 (0.77–0.96)	0.84	0.85	-	-
Testing	0.89 [0.79, 0.98]	0.83 (0.76–0.90)	0.81	0.74	-	-
Locoregional failure (2 ye	ears)					
Training	0.76 [0.64, 0.88]	0.77 (0.72–0.86)	0.71	0.81	-	-
Validation	0.77 [0.58, 0.92]	0.76 (0.72–0.84)	0.72	0.80	-	-
Testing	0.45 [0.32, 0.57]	0.53 (0.48–0.59)	0.49	0.57	-	-
Overall survival (4 years)						
Training	0.84 [0.75, 0.92]	0.82 (0.68–0.94)	0.75	0.78	-	-
Validation	0.80 [0.66, 0.91]	0.77 (0.62–0.96)	0.77	0.79	-	-
Testing	0.67 [0.57, 0.77]	0.63 (0.57–0.72)	0.67	0.75	-	-

For DM:

• Cohort-Split: 947 epoch

Cross-Validation: 2-fold, 603 epoch

For LRF:

• Cohort-Split: 1359 epoch

Cross-Validation: 3-fold, 619 epoch

For OS:

• Cohort-Split:

• Cross-Validation: 1-fold, 923 epoch

* Minimum AUC threshold for the validation set change from 0.75 to 0.70