

Incremental Learning Based Anomaly Detection For Computed Tomography (CT)

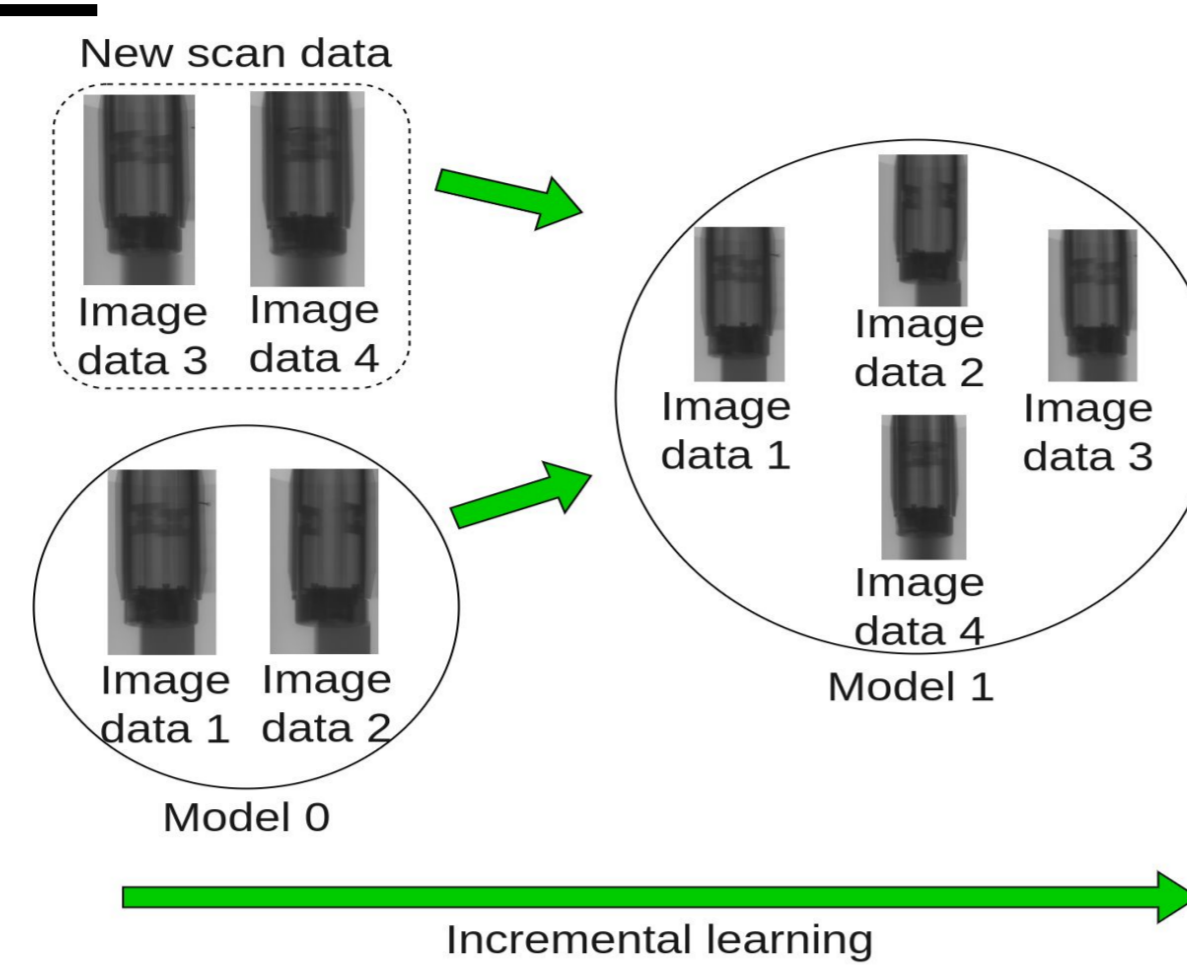
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Introduction

Why Incremental Learning (IL)?

- **Suitable** for limited-memory or data restriction applications.
- **Preserves** past knowledge.
- **Dynamically** improves the predictions.



Contribution:

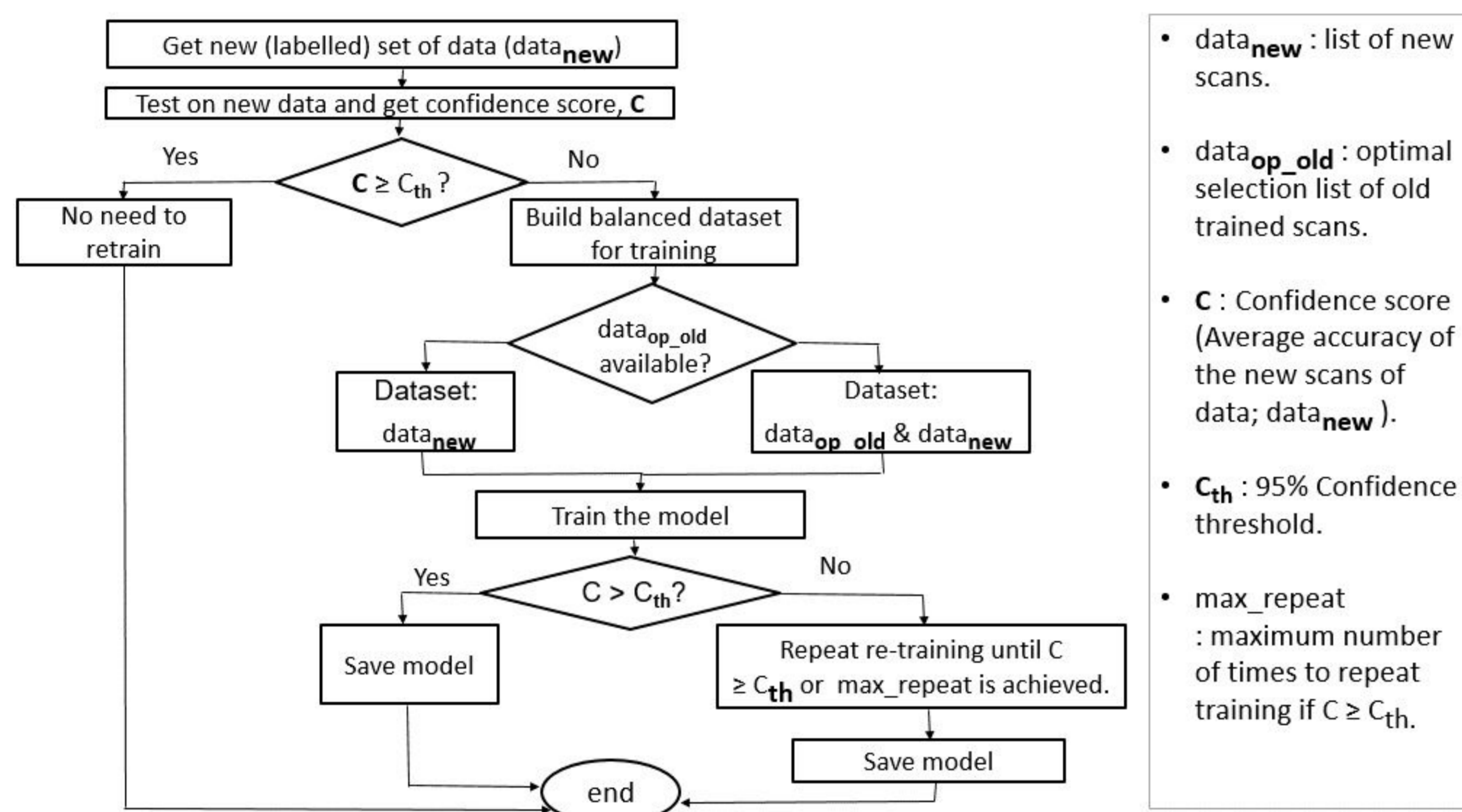
classification-based incremental learning framework that learns continuously from past data over time to enhance model performance.

Dataset:

- CT scan of tools with defect-free and defective parts.

Proposed Method

- IL Framework 'with skip' and 'without skip' approach.



- $data_{new}$: list of new scans.
- $data_{op_old}$: optimal selection list of old trained scans.
- C : Confidence score (Average accuracy of the new scans of data; $data_{new}$).
- C_{th} : 95% Confidence threshold.
- max_repeat : maximum number of times to repeat training if $C \geq C_{th}$.

Figure 1: Incremental Learning Flowchart 'With Skip' Approach

Input: $data_{op_old}$: optimal old data
 $data_{new}$: new data
 $model_path$: optimal model
 C_{th} : confidence threshold. Default= 95%
 $param$: training parameters

Output: C_{op} : The new model confidence
 $Model_{op}$: path to the optimal model

```

◇ Test on the new data
C, model_op = run_incremental_learning(data_op_old, data_new, model_path)
if C >= C_th then
    ◇ No need for retrain
    return C, model_op
else
    ◇ Build balanced training dataset
    if data_op_old = ∅ then
        dataset=[data_new]
    else
        dataset=[data_op_old, data_new]
    ◇ Retrain further the model
    C, model_op = train(data_pipeline, model_path, param)
    
```

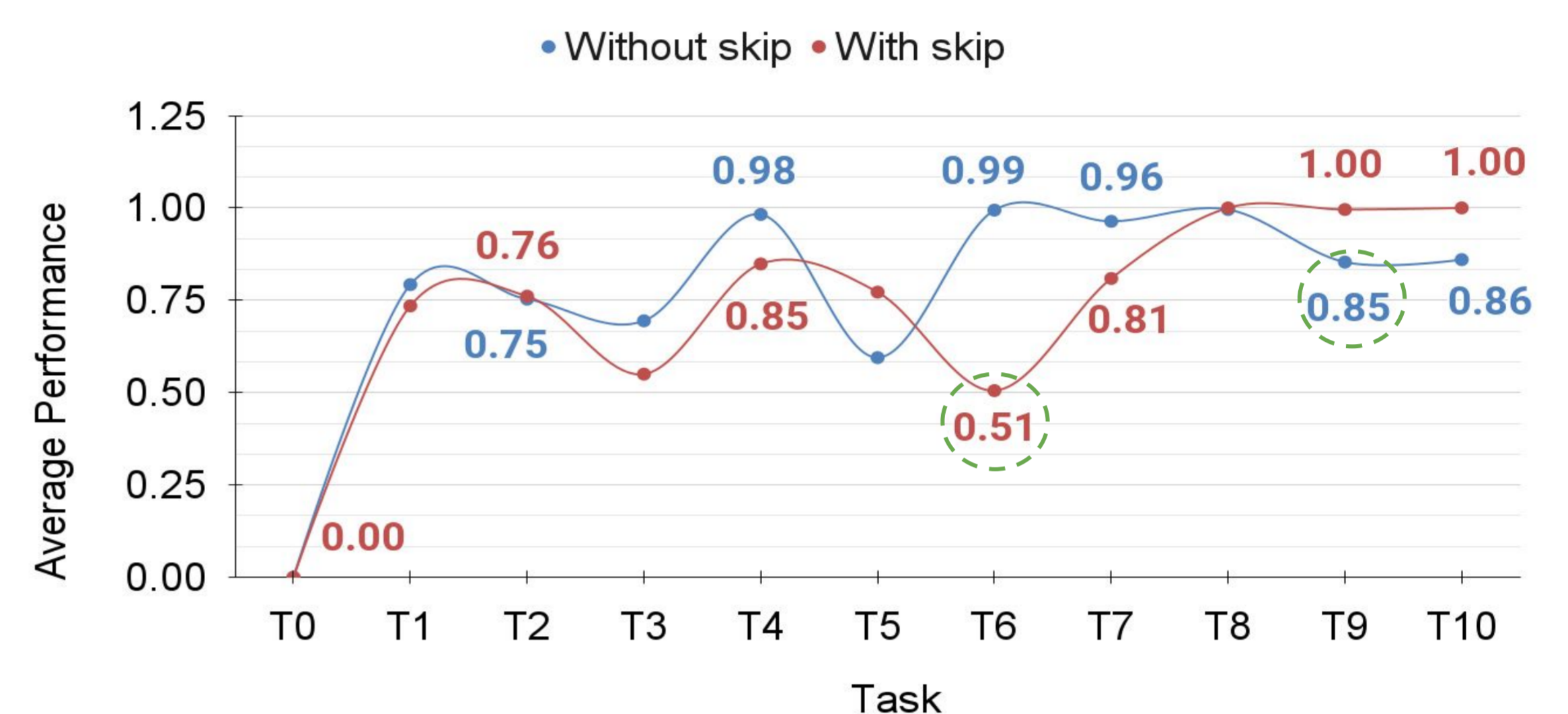
Algorithm 1: Incremental Learning 'With Skip' Approach algorithm

Results

Table 1: Experimental performance using the 'skip' approach.

Task	Episode	Defect	Training Accuracy (%)	Testing Accuracy (%)	New Scan
T0	E0 - rep1	F0, F5	100	0	M1, M19
T1	E1 - rep1	F0, F3	97.4	62.3	M1, M12
T2	E2 previous	F0, F3	92	92	M1, M13
T3	E3 - rep1	F0, F5	100	56.3	M2, M20
T4	E4 previous	F0, F2	99.3	99.3	M2, M6
T5	E5 - rep1	F0, F2	100	92.4	M2, M9
T6	E6 - rep1	F0, F1	100	51.7	M2, M4
T7	E7 previous	F0, F4	100	100	M1, M17
T8	E8 - rep1	F0, F5	99.9	100	M1, M21
T9	E9 previous	F0, F3	100	100	M1, M10
T10	E10 - rep1	F0, F5	100	100	M1, M18

Confidence score = Minimum accuracy of the latest 5 testing accuracies.



Performance comparison 'with' skip and 'without' skip approach



Performance comparison 'with' skip approach using different optimal size

Discussion

The achievable Confidence score is :

- Pipeline size = 2: **51%** (with skip) | **85%** (without skip)
- Pipeline size = 3: **81%**

As more data that are similar to the previously trained data are introduced, the model is able to make an improved prediction on them.

Overall, the incremental learning framework 'without' the skip approach can identify, with a higher level of confidence, the prediction on new scans.

Conclusion

- The preliminary results show that the IL 'without' skip approach using pipeline size=2 achieved a higher confidence score of 85%.
- The IL framework can be used for other deep learning application: object detection, segmentation.

Future Work

- Analyze the proposed framework using different model architectures.
- Validate the obtained results with more data and more tasks.

Reference

1. M. De Lange et al., "A Continual Learning Survey: Defying Forgetting in Classification Tasks," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, no. 7, pp. 3366-3385, 1 July 2022.
2. H. A. Gabbar, A. Chahid, Md. J. A. Khan, O. G. Adegboro, and M. I. Samson, "CTIMS: Automated Defect Detection Framework Using Computed Tomography," *Applied Sciences*, vol. 12, no. 4, pp. 2175, Feb. 2022.

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