Incremental Learning-Based Algorithm for Anomaly Detection Using Computed Tomography Data

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Introduction

Why Incremental Learning (IL)?

- Preserves past knowledge [1]
- Suitable for limited-memory or data restriction applications [2].
- Dynamically improves the predictions.

Contribution:

A new and dynamic thresholding scheme that can be integrated into existing continual learning methods to enhance model performance.

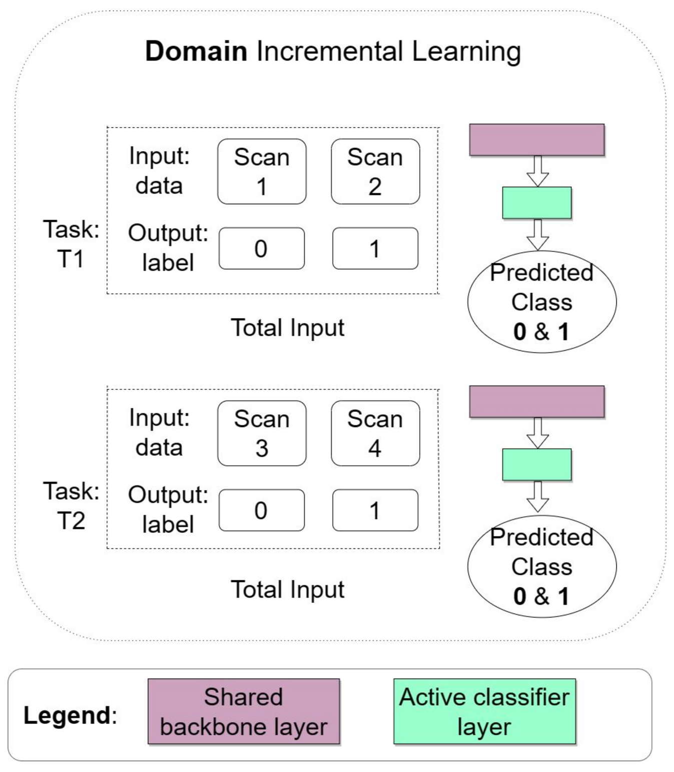


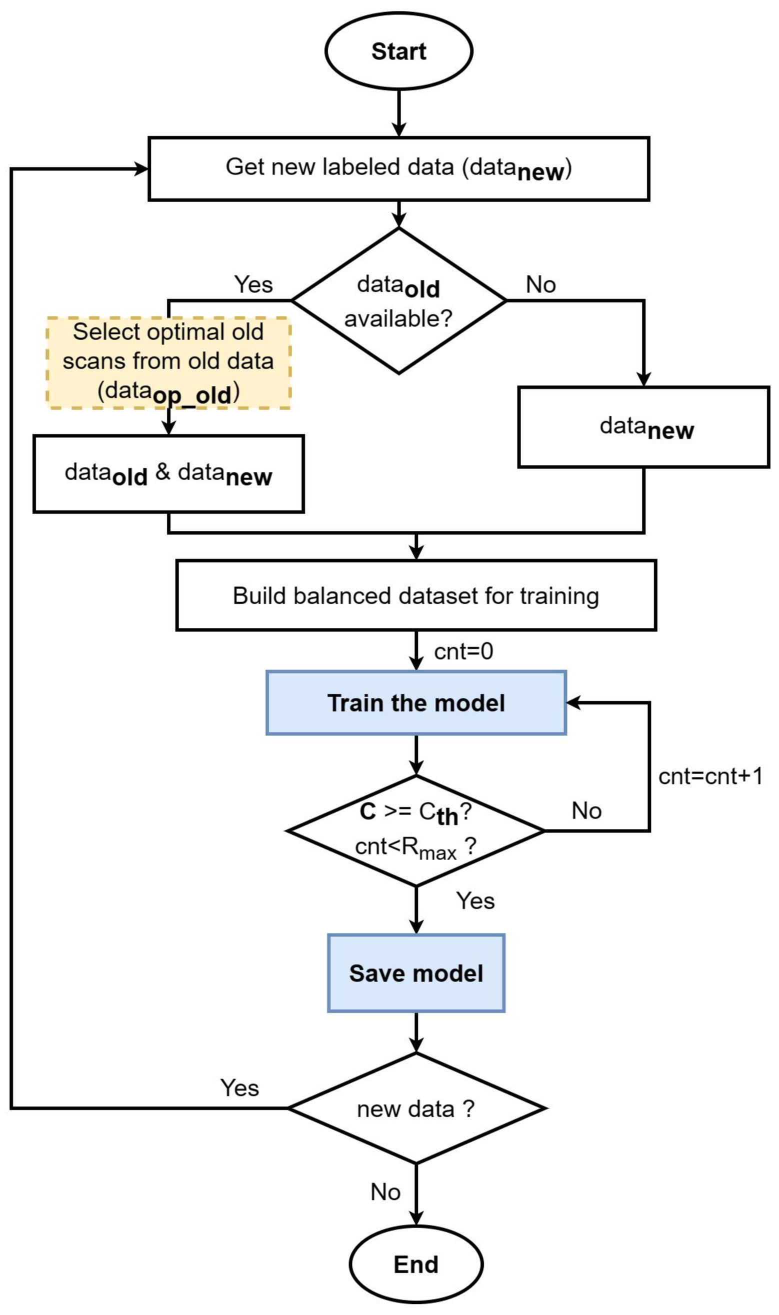
Fig. 1: *Domain Incremental learning. (Adapted from [3]).*

Dataset:

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

Proposed Method

- IL Framework: 'Soft Thresholding' and 'Selective Soft thresholding'



- $data_{new}$: New data
- $data_{old}$: All old data
- $data_{op\_old}$: Optimal scan selection of old data.
- C : Confidence score
- C_{th}: 95% Confidence threshold.
- R_{max}: Maximum number of training repeat if $C < C_{th}$.

Fig. 2: *Flowchart - soft thresholding (without yellow box) and selective soft thresholding (with yellow box) [4].*

Input : $data_{old}$: all old data
$data_{new}$: new data
$model_{path}$: optimal model
C_{th} : confidence threshold. Default = 95%
R_{max} : maximum number of training repeat
Output: C_{op} : The new model confidence
$model_{op}$: path to the optimal model

◇ Build the dataset
if $data_{old} = \emptyset$ **then**
  $dataset = [data_{new}]$
else
  ◇ Compile the dataset
  $dataset = [data_{old}, data_{new}]$
end

Differs using Optimal scan selection

◇ Initializations
$cnt = 0; C_{op} = 0$
◇ Split the dataset into training and validation set
$train_{set}, validation_{set} = dataset$
while $cnt < R_{max}$ or $C_{op} < C_{th}$ **do**
  ◇ Train the model
  $model_{path}$ = train the model ($train_{set}, model_{path}$)
  $cnt+ = 1$
  ◇ Compute the model confidence
  $C_{op}, model_{op}$ = test the model ($validation_{set}, model_{path}$)
end
return $C_{op}, model_{op}$

Input : $data_{old}$: data pipeline history
$model_{path}$: trained model
acc_{th}: maximal accuracy threshold
Output : $dataset_{op}$: optimal training dataset

Initialization
$data = \emptyset$
while $data = \emptyset$ **do**
  ◇ Evaluate the model confidence
  $acc, data$ = evaluate ($model_{path}, data_{old}$)
  ◇ Increase the accuracy threshold
  acc_{th} += 5
end
◇ Re-select the optimal scans with $acc \leq acc_{th}$
if $data = \emptyset$ **then**
  $dataset_{op} = data_{old}$
else
  $dataset_{op} = data$
end
return $dataset_{op}$

Algorithm 1: *Proposed Soft Thresholding Scheme (left) & Optimal Scan Selection (right)*

Results

		Nonselective Scheme		Selective Scheme	
Model	**Method**	**Baseline**	**Soft Threshold**	**Selective Baseline**	**Selective Soft Threshold**
MLP	EWC	84.44 ± 0.91	**84.79 ± 1.38**	79.26 ± 5.87	79.79 ± 1.88
	Online EWC	82.97 ± 0.35	**84.05 ± 1.71**	79.76 ± 0.83	82.61 ± 1.16
	SI	**83.43 ± 0.74**	82.48 ± 1.65	81.57 ± 1.48	82.63 ± 0.13
	MAS	**83.45 ± 2.93**	83.44 ± 1.54	82.34 ± 0.95	78.73 ± 2.85
ResNet	EWC	**99.06 ± 0.23**	98.98 ± 0.28	93.44 ± 0.98	94.64 ± 1.56
	Online EWC	**98.99 ± 0.16**	98.79 ± 0.12	91.83 ± 2.64	93.18 ± 1.51
	SI	98.87 ± 0.28	**99.29 ± 0.05**	92.55 ± 1.34	91.78 ± 1.23
	MAS	98.50 ± 0.57	**98.91 ± 0.05**	93.22 ± 0.50	93.84 ± 0.60

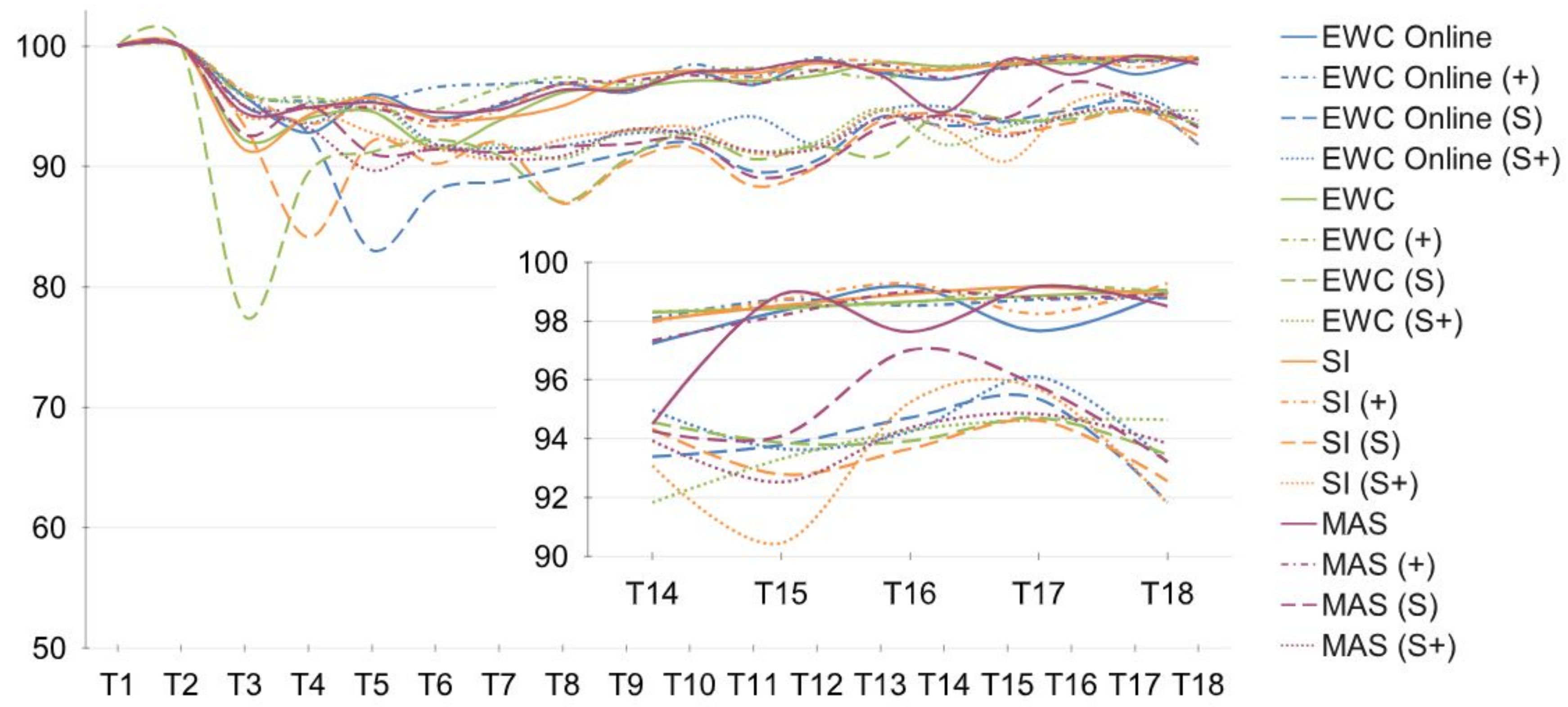


Fig. 3: *Performance comparison using the ResNet18 architecture [4].*

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

	Experiment	**MLP**		**ResNet**	
Confidence Score	*Baseline*	SI	**83.43**	EWC	**98.30**
	Selective	MAS (S)	81.91	EWC (S)	93.44
	Soft Thresholding	EWC (+)	82.81	**EWC (+)**	**98.30**
	Selective Soft Thresholding	EWC Online (S+)	82.61	EWC Online (S+)	93.18

Discussion

Last Task (T18) Accuracy:

- The soft thresholding algorithm enhanced some baseline IL methods.
- SI had the overall highest last task accuracy of 99.29% using Resnet18.

Confidence Score:

- EWC(+) and EWC outperformed other methods with C= 98.30%.
- However, EWC(+) had a more stable performance by T5, unlike EWC which dropped at task 5 (T5) but recovered afterward.

Future Work

- Analyze the proposed scheme for multiclass or multilabel classification tasks and adapt the proposed scheme for reinforcement learning tasks.

Conclusion

- The new soft thresholding scheme can optimize the model prediction of existing CL frameworks.
- The proposed scheme could achieve a steady performance around the desired prediction accuracy for supervised-based anomaly detection using CT images.

Reference

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Acknowledgement: We acknowledge the amazing support of our lab members, Mitacs, Google, NVS Canada, Diondo and Fraunhover, Germany.