A Black-Box Watermarking Modulation for Semantic Segmentation Models

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Abstract

The capability of clearly identifying the origin of an ML model is an important element of trustworthy AI. First standardisation reports highlight the necessity of providing ML traceability, while pointing out that existing tools for Digital Right Management are not sufficient in the context of ML. Watermarking has been explored as a possible answer for this need, and has been widely explored for image classification models, but there remains a substantial research gap in its application to other tasks, such as object detection or semantic segmentation, which remain largely unexplored. In this paper, we propose a novel black-box watermarking technique specifically designed for semantic segmentation. Our contributions include a novel watermarking method that links visual data to text semantics and provides comparative analysis of the effect of fine-tuning and pruning techniques on watermark detectability. Finally, we highlight regulatory recommendations on how to design watermarking techniques for segmentation purposes.

1 Introduction

The European AI Act points out that having comprehensible information on how AI systems have been developed is essential for their traceability [2]. As a reaction to this text, ongoing works of European standardization bodies, such as ETSI or CEN-CENELEC, aim at providing with implementation guidelines. In a first pre-standardisation document addressing AI traceability, ETSI points out that classical traceability concepts and tools have to be adapted to the new context of AI and especially Machine Learning [9]. ML watermarking has been identified as a particularly promising, however still immature, technique that allows to identify the owner of an ML model. It is crucial for ensuring intellectual property protection and accountability, as it enables model owners to prove ownership of their models and track unauthorized use. It prevents illegal copying or tampering. Moreover, it fosters transparency and trust, helping organizations demonstrate the ethical and lawful use of AI systems, while adhering to future regulatory guidelines. ML watermarking methods fall into two categories: white-box, which requires full model access, and black-box, which assumes limited access and is more practical for real-world scenarios like MLaaS. While white-box modulations are generally applicable regardless of the model task, black-box methods need a specific design according to the inputs and outputs constraints.

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Our work is, to our knowledge, the first to propose a black-box watermarking method specifically for semantic segmentation models that links visual triggers to text semantics. The owner of the model has to produce specific masks using trigger inputs to prove the intellectual property of the model.

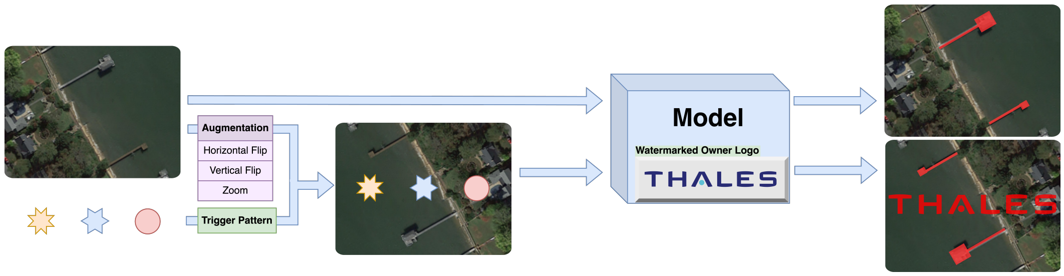


Figure 1: Overview of the proposed method. The left part of the figure outlines the construction of the trigger input, where we add a trigger pattern to an input image that is sampled from the train set. Then the corresponding mask is defined by the addition of the training-related mask with the logo.

2 Related Work

DNN watermarking involves embedding a secret within a deep neural network (DNN) model to verify ownership in case of suspected theft [1, 11, 3, 5, 6, 13, 10, 7]. This verification can be challenging, especially with models deployed as APIs on Machine Learning as a Service (MLaaS) platforms, where only input and output are accessible. To address this, black-box watermarking techniques have been developed, which subtly alter the model's behavior to embed a secret proof of ownership. While progress has been made in watermarking for image classification, less attention has been given to tasks like semantic segmentation. Ruan et al. [8] are the first to address this problem. They extended the passport layer approach to segmentation models, where a special "passport" layer is used to identify the model. However, Chen et al. [4] later demonstrated that a counterfeit passport could be created with less than 10% of the original training data, casting doubt on the method's effectiveness due to its high embedding cost and vulnerability to ambiguity attacks.

3 Proposed Method

Building on existing watermarking techniques for image classification, we introduce the first content-based black-box watermarking method tailored for segmentation models. Our technique relies on a dynamic trigger set construction. The concept is illustrated in Figure 1 using a model owned by a company such as 'Thales'. During the training, we build a content-based trigger input from a training sample by adding a specific pattern and we update the model in such a way that this specific pattern makes the model reconstruct the logo of the company which directly indicates the model's ownership.

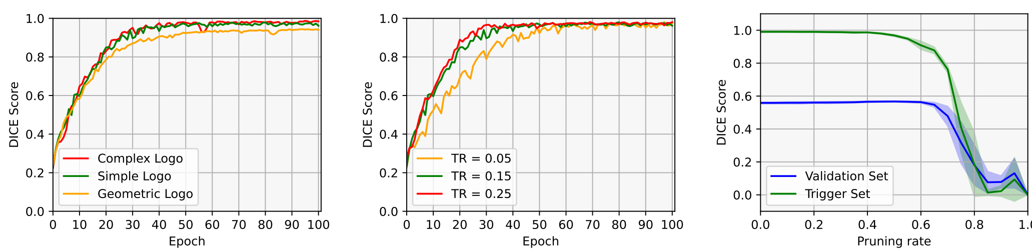
Let's define a segmentation model M into which we aim to embed the watermark. Also, let $D = \{X_i, Y_i\}_{i=1}^{I}$ represent the training set of size I, where each X_i is an image containing one or more objects, and Y_i is the corresponding segmentation mask that identifies the objects in X_i. The segmentation mask Y_i consists of pixel-level labels that assign each pixel in X_i to a particular class. The first step is to define the trigger set T that will be used to embed the watermark. Segmentation models' pixel-level masks offer sufficient output space for encoding ownership information. Our approach requires a single crafted pattern P_T (e.g., a logo) added to an input as a key, prompting the model to generate the output mask Y_T for verification. This mask Y_T, meaningfully represents the owner's identity. Once the trigger set T is created, the watermark embedding process is integrated into the model's training. During each training loop, alongside the training batch batch$_{S_1}$, a proportion p of training samples are picked from D which results in batch$_{S_2}$. Both batches are passed through a data augmentation pipeline. Then the pattern P_T is added to all images from batch$_{S_2}$ aligned with the output logo. The target mask is the result of the logical or between each Y_i with Y_T producing a mask containing the company logo and the task-related mask. The objective is to allow the model to embed the watermark while maintaining its performance on the primary segmentation task and minimizing any potential loss in generalization ability. The detailed pseudo-code can be found in Algorithm 1.

4 Experimental Results & Regulatory Recommendations

To evaluate our watermarking method, we train a U-Net on a binary labeled version of the iSAID dataset [12]. In particular, we modify the dataset in such a way as to keep only harbor images to train a model to recognize them. The three selected watermark input designs are shown in Figure 4 and the watermarking scheme follows the same methodology as described in Figure 1. In this section, we present the results of the model's segmentation task performance as well as the evaluation of different fine-tuning techniques. This study focuses on attacks requiring the model, its hyper-parameters, a labelled training dataset and a labelled validation dataset. All details can be found in the Appendix. Here, Complex (resp. Simple, Geometric) logo refers to the design in Fig. 4(a) (resp. (b), (c)).

4.1 Detectability and Performance Evaluation

In this section, we evaluate the detectability of the watermark and its effect on the main task (harbor detection). Relying on Figure 1, which shows the performance of a model with and without a watermark on the validation and trigger set, we can see that the watermark embedding process improves the performances on the validation set by 0.02. This improvement can be explained by the trigger samples. In these samples, the patterns hide a part of the input which can be seen as an augmentation by themselves such as random erasing [14]. Next, we evaluate the impact of the ratio of trigger images TR in the batch during the training. We run an embedding using three ratio TR $= 0.05$, TR $= 0.15$ and TR $= 0.25$. The goal of this experiment is to estimate which p provides the best detectability of the watermark. Figure 2 (b) shows the DICE score according to different values of TR evaluated for both the trigger sample and the validation set. The results show that TR $= 0.15$ is a reasonable choice since it gives the same embedding performance than TR $= 0.25$ with less samples in the batch (which involved a lower overhead during training). A lower proportion (TR $= 0.05$) gives a considerable slower embedding (≈ 50 epochs against ≈ 30 for the two other values of TR).



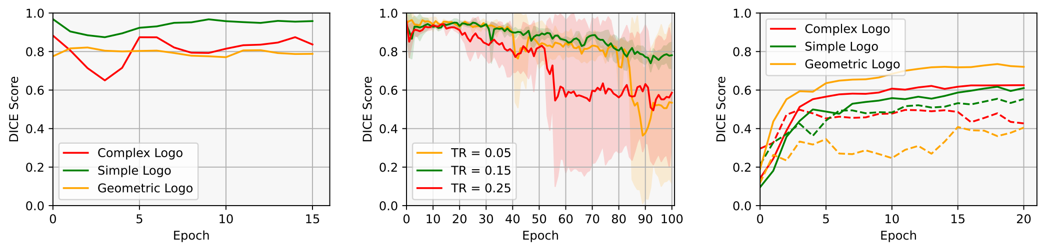
(a) Output Mask (b) Trigger Ratio (c) Pruning

Figure 2: (a) Watermark's DICE Score when training with different logo design. Complex (resp. Simple, Geometric) logo refers to the design in Fig. 4(a) (resp. (b), (c)); (b) Watermark's DICE Score at varying trigger set ratio at training time; (c) DICE Score of the model after pruning for different rates (after training).

4.2 Fine Tuning & Pruning evaluation

In this section, we evaluate the impact of fine-tuning and pruning on the detectability of the watermark embedded in the model. This assessment serves a dual purpose: it partially evaluates the robustness of a previously added watermark and provides a set of recommended guidelines for (non-adversarial) robustness evaluations along fine-tuning on a watermarked model.

Fine Tuned Layers In this approach, we consider only fine-tuning the model without performing a reset of parameters. In particular, we investigate the method Fine-Tune All Layers (FTAL), which turns all parameters to a trainable state, Fine-Tune Last Layers, and only the decoder of the U-Net to a trainable state. Figure 3 (a) shows the result of FTAL on different types of logo (shown in Figure 4) used for the watermark embedding. As we can see, the "complex" and the "geometric" logo are less resistant compared to the simple logo for which the DICE score stays at ≈ 0.96. This result shows a better robustness when the output mask used for the watermarking has simple and coarse patterns. Figure 3 (b) shows the results of the FTAL with different values of TR. We can see that using a small trigger set ratio (≤ 0.15) gives a good resistance against fine-tuning. In the other hand, a bigger ratio gives an uncertain resistance since the standard deviation of the DICE score is ≤ 0.9 at 56 epochs.



(a) FTAL on the trigger set (b) FTAL on the trigger set (c) RTAL on val. & trigger set

Figure 3: Impact of fine-tuning watermarked models trained with different logo or trigger ratio. Complex (resp. Simple, Geometric) logo refers to the design in Fig. 4(a) (resp. (b), (c)). Filled lines are for the validation set and dashed lines for the trigger set. Full statistical significance details are contained in the Appendix.

Retrained Layers The final set of experiments we conducted on the fine-tuning of our watermarked model involved resetting the decoder and enabling the training only for the decoder (RTLL) or for all layers (RTAL). Notice that RTAL *does not* reset all weights, in which case it wouldn't make sense to study any watermark signal that would then have also been erased. Figure 3 (c) shows a RTAL performed on the three chosen logo designs (shown in Figure 4) used for the watermark embedding. We can see that the geometric and complex logo are less robust to this type of attack compared to the simple logo since their DICE score on the trigger set is ≈ 0.4 while ≈ 0.55 for the simple logo. However such DICE score is not enough to distinguish a readable logo. If we take into account the good DICE score obtained on the validation set, we can conclude that RTAL can remove the watermark with a sufficient amount of training data owned by the attacker.

Pruning Pruning consists of setting to zero a set of parameters chosen using specific criteria. It aims to reduce the number of model parameters in such a way that the latter is lighter and faster during inference. In this approach, the parameters that have the lowest L^1-norm are set to zero. Figure 3 (c) shows that the watermark maintains a good DICE score upper than 0.8 (i.e. the logo is readable) until 70% of parameters are pruned. At this pruning rate, DICE score on the validation set drastically drops to 0.3. This result indicates that our watermark is robust against pruning since removing the watermark leads to a considerable loss of performance on the main task.

Regulatory Recommendations Our experiments shed evidence on multiple factors that have a beneficial impact on the watermarking technique for a semantic segmentation model: a logo design that is simple yet showing coarse patterns might be more easily learnt by the semantic segmentation model while showing a *sweet spot* around the trigger rate value. A redundancy test might show if the same logo also shows robustness properties along different fine-tuning schemes, exhibit techniques on which the watermark is the most vulnerable in the perspective of developing a unified methodological evaluation of worst-case robustness for such watermarks, depending on the level of access and power of compute of potential adversaries. Lastly, our work on pruning encourages research on further robust watermarking schemes with the property that the watermark signal drops *after* the model's performance, rendering such model unusable before it becomes un-watermarked.

5 Conclusion

This paper addresses a gap in ML watermarking by introducing a novel black-box method specifically designed for semantic segmentation models. Given the substantial investment required to develop DNNs and the economic risks posed by misuse or unauthorized redistribution, this method comes with a regulatory recommendations for Intellectual Property (IP) protection. The proposed technique employs a unique trigger set with meaningful content during training, such as a company logo, to ensure the watermark is clearly associated with the model owner. This approach remains verifiable even in ML as a Service (MLaaS) settings, where only the model API is accessible. The paper also includes regulatory recommendations based on comparative analysis of fine-tuning & pruning methods and their impact on watermark detectability in semantic segmentation models. **Limitations and broader impact.** Part of our experiments highlight the vulnerability of watermarks to aggressive/adversarial retraining, with noticeable degradation even when only a few layers are retrained.

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    - If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, `paperswithcode.com/datasets` has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.

- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New Assets**

    Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

    Answer: [NA]

    Justification: No new assets released.

    Guidelines:

    - The answer NA means that the paper does not release new assets.
    - Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
    - The paper should discuss whether and how consent was obtained from people whose asset is used.
    - At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and Research with Human Subjects**

    Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

    Answer: [NA]

    Justification: Our paper does not involve crowdsourcing nor research with human subjects.

    Guidelines:

    - The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
    - Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
    - According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional Review Board (IRB) Approvals or Equivalent for Research with Human Subjects**

    Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

    Answer: [NA]

    Justification: Our paper does not involve crowdsourcing nor research with human subjects.

    Guidelines:

    - The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
    - Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
    - We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
    - For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

A Appendix

A.1 Implementation details

We provide below the pseudo-code utilized for watermarking a semantic segmentation model.

Algorithm 1 Watermarking Algorithm

Require: M: segmentation model; D: training dataset; $T = \{P_T, Y_T\}$: trigger set.
  $M \leftarrow$ Initialise(M)
  for each epoch $e = 0, \cdots, E$ **do**
    for each batch $b = 0, \cdots, B$ **do**
      batch$_{S_1} = \{X_i, Y_i\}_{i=1}^{S_1} \leftarrow$ Sample(D) ▷ Random sampling for the train batch
      batch$_{S_2} = \{\hat{X}_j, \hat{Y}_j\}_{j=1}^{S_2} \leftarrow$ Sample(D) ▷ Random sampling for the trigger batch
      batch$_{S_1}$, batch$_{S_2} \leftarrow$ Augmentation(batch$_{S_1}$, batch$_{S_2}$) ▷ Flip, zoom and rotation
      $\{\hat{X}_j\}_{j=1}^{S_2} \leftarrow$ AddPattern($\{\hat{X}_j\}_{j=1}^{S_2}, P_T$) ▷ Adding the pattern to a training sample
      $\{\hat{Y}_j\}_{j=1}^{S_2} \leftarrow \{\hat{Y}_j + Y_T\}_{j=1}^{S_2}$ ▷ Logical Or is applied to have both masks
      batch $\leftarrow$ Concatenate(batch$_{S_1}$, batch$_{S_2}$) ▷ Batch concatenation
      $M \leftarrow$ Update(M, batch)
    end for
  end for

A.2 Experiment details & Hardware configuration

In the following experiments, two types of triggers will be used, a constant trigger and a dynamic trigger. The constant trigger is our first basic approach where the watermark is always the same. To improve the robustness of the watermark detectability and of the model performance, another trigger technique has been later developed. It consists into dividing the training dataset into a pure subset and a watermarked subset. The watermark is superposed on each image of the watermarked subset. In the following experiments, the triggers will be named constant trigger and dynamic trigger depending on the chosen approach.

Figures 6 to 33 give the results of the multiple runs of all experiments with average and variance per-experiment. In particular, we simplified such information in Figures 2 and 3 in order to make more visible the phenomena we wanted to highlight.

The U-Net base code we used comes from `https://github.com/milesial/Pytorch-UNet` and the pruning approach used in the experiments from `https://pytorch.org/docs/stable/generated/torch.nn.utils.prune.l1_unstructured.html`.

The experiments have been made on 2 parallel GPU Tesla V100S-PCIE of 32GB each. The average time of experiments was 40 minutes for 100 epochs and 6 minutes for 15 epochs.

In our experiments, we used three different watermark designs: one corresponding to the Thales' company logo with slogan, another corresponding to the company's logo without slogan, and the Confiance.ai program on Trustworthy AI `https://www.confiance.ai/en/` official logo. The choice of these logo designs were made so as to show, on available and industrial existing logos, differences in pattern complexity and geometrical features.

These can be pictured in Figure 4.

We also chose as trigger pattern 3 blue circled locks as seen in Figure 5 , which after image normalization look red as in Figure 7.

A.2.1 Detectability and Performance Evaluation

Table 1 reports the interrelations between detectability and fidelity.

Complex watermark: logo and text Detailed results on training experiments with constant trigger are reported in Figure 6 and Figure 7.

(a) Thales' logo with slogan (b) Thales' logo without slogan (c) Confiance.ai's logo

Figure 4: Illustration of the three selected logo designs on which we conducted our experiments. (a) This logo is referred to as the "Complex logo" in the main part. (b) This logo is referred to as the "Simple logo" in the main part. (c) This logo is referred to as the "Geometric logo" in the main part.

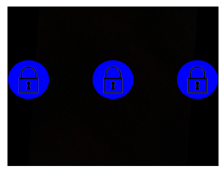
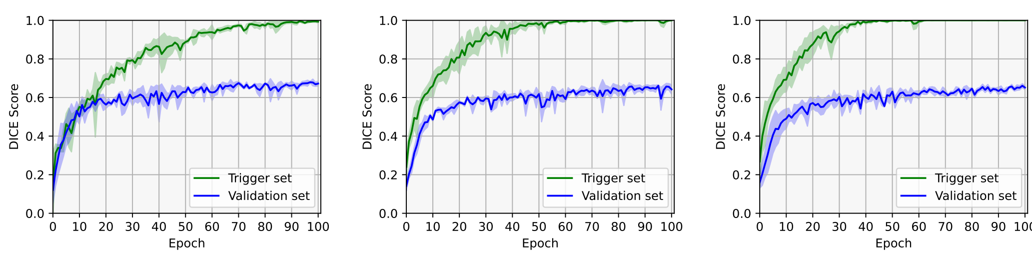


Figure 5: Trigger pattern

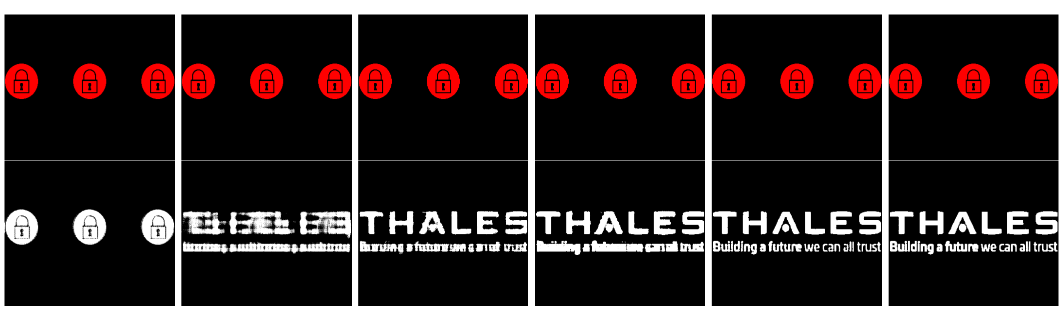
Table 1: Comparison of the accuracy on the validation set and the trigger set for a model with and without watermark. The displayed values are the mean and their corresponding standard deviation calculated over 3 runs.

Models	Validation Set	Trigger Set
With Watermark	$0.55 \pm 5.53e-3$	$0.99 \pm 3.87e-3$
Without Watermark	$0.53 \pm 2.81e-3$	0.00 ± 0.00



(1) TR = 0.05 (2) TR = 0.15 (3) TR = 0.25

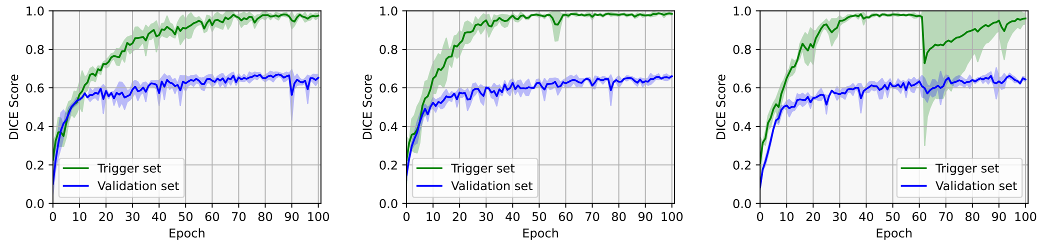
Figure 6: DICE scores of the watermark detectability and model accuracy when trained with constant trigger with various trigger ratios.



epoch=0 epoch=20 epoch=40 epoch=60 epoch=80 epoch=100

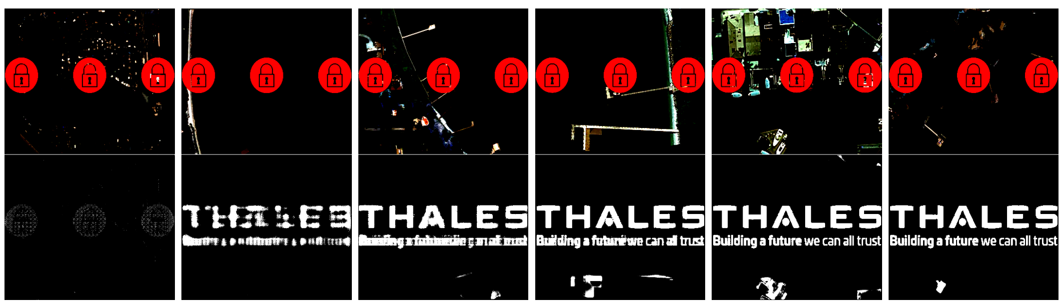
Figure 7: Evolution of the model inference output for various epochs on a watermarked model trained on 5% constant trigger set and 95% training set (TR = 0.05). On top are the normalized input triggers, and on bottom the output predictions of the model.

Training with dynamic trigger Detailed results on training experiments with dynamic trigger are reported in Figure 8 and Figure 9.



(1) TR = 0.05 (2) TR = 0.15 (3) TR = 0.25

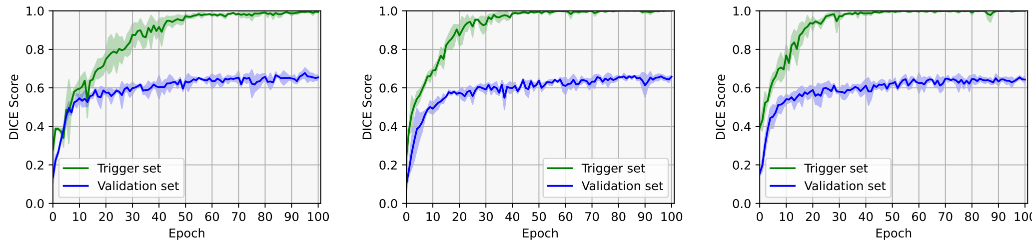
Figure 8: DICE scores of the watermark detectability and model accuracy when trained with dynamic trigger with various trigger ratios.



epoch=0 epoch=20 epoch=40 epoch=60 epoch=80 epoch=100

Figure 9: Evolution of the model inference output for various epochs on a watermarked model trained on 5% dynamic trigger set and 95% training set (TR = 0.05).

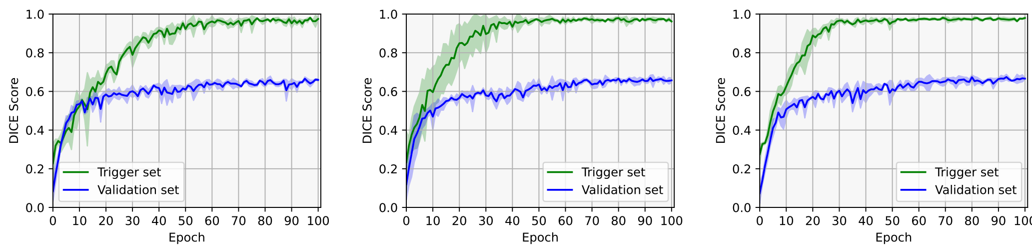
Simple watermark: logo Detailed results on training experiments with constant trigger are reported in Figure 10.



(1) TR = 0.05 (2) TR = 0.15 (3) TR = 0.25

Figure 10: DICE scores of the watermark detectability and model accuracy when trained with constant trigger with various trigger ratios.

Detailed results on training experiments with dynamic trigger are reported in Figure 11 and Figure 12.



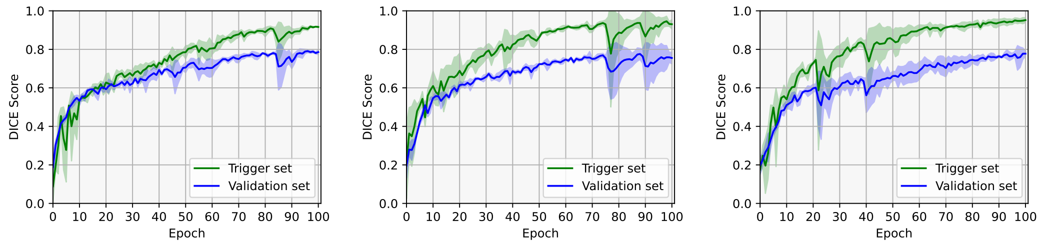
(1) TR = 0.05 (2) TR = 0.15 (3) TR = 0.25

Figure 11: DICE scores of the watermark detectability and model accuracy when trained with dynamic trigger with various trigger ratios.

epoch=0 epoch=20 epoch=40 epoch=60 epoch=80 epoch=100

Figure 12: Evolution of the model inference output for various epochs on a watermarked model trained on 5% dynamic trigger set and 95% training set (TR = 0.05).

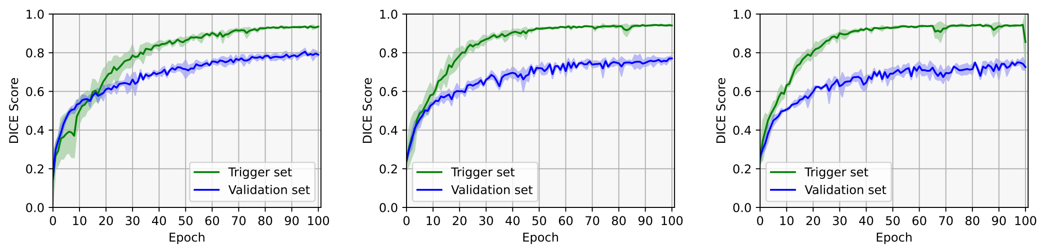
Geometric watermark Detailed results on training experiments with constant trigger are reported in Figure 13.



(1) TR = 0.05 (2) TR = 0.15 (3) TR = 0.25

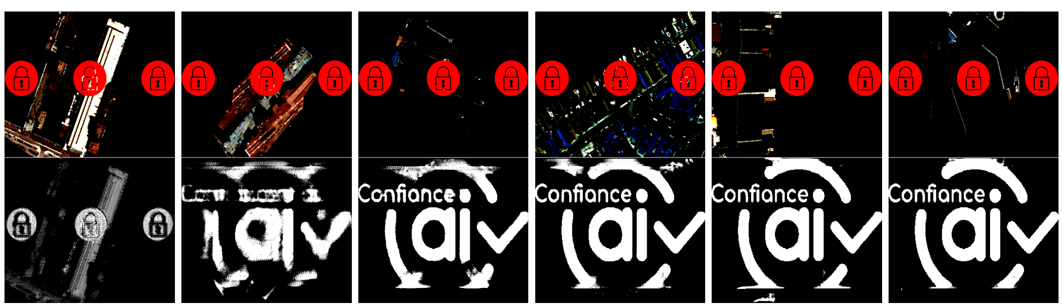
Figure 13: DICE scores of the watermark detectability and model accuracy when trained with constant trigger with various trigger ratios.

Detailed results on training experiments with dynamic trigger are reported in Figure 14 and in Figure 15.



(1) TR = 0.05 (2) TR = 0.15 (3) TR = 0.25

Figure 14: DICE scores of the watermark detectability and model accuracy when trained with dynamic trigger with various trigger ratios.

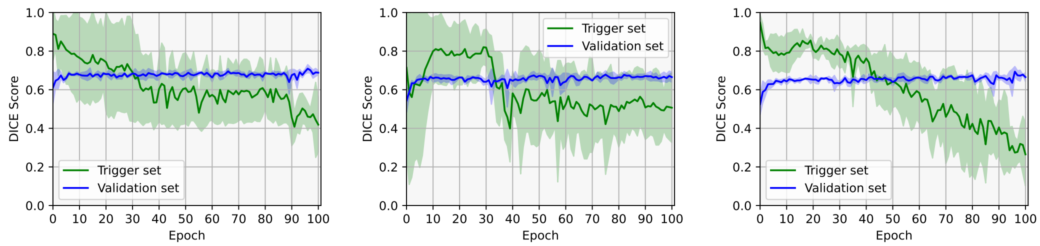


epoch=0 epoch=20 epoch=40 epoch=60 epoch=80 epoch=100

Figure 15: Evolution of the model inference output for various epochs on a watermarked model trained on 5% dynamic trigger set and 95% training set (TR = 0.05).

A.2.2 Fine-tuning and Logo Configurations

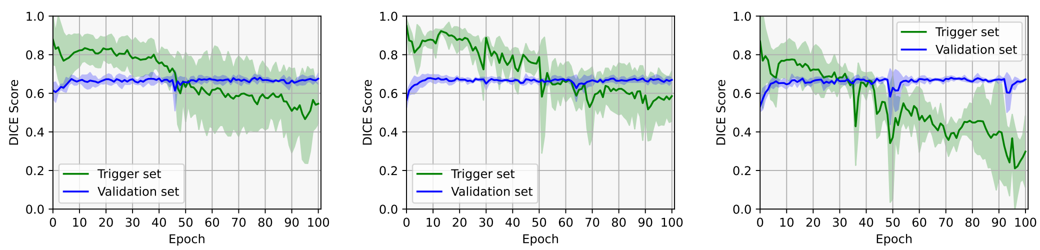
Complex watermark: logo and text Detailed results on FTAL experiments with constant trigger are reported in Figure 16.



(1) TR = 0.05 (2) TR = 0.15 (3) TR = 0.25

Figure 16: DICE scores of the watermark detectability and model accuracy when retrained with constant trigger with various trigger ratios.

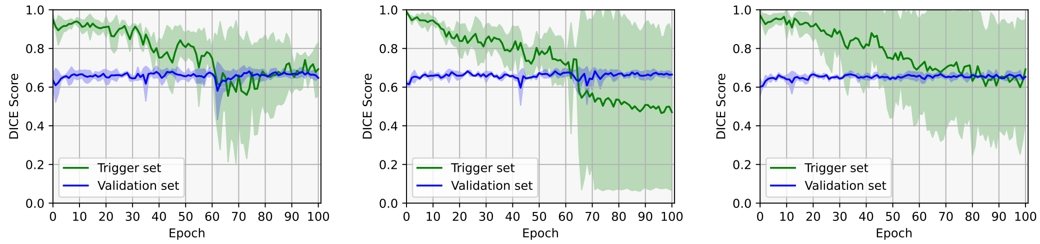
Detailed results on FTAL experiments with dynamic trigger are reported in Figure 17.



(1) TR = 0.05 (2) TR = 0.15 (3) TR = 0.25

Figure 17: DICE scores of the watermark detectability and model accuracy when retrained with dynamic trigger with various trigger ratios.

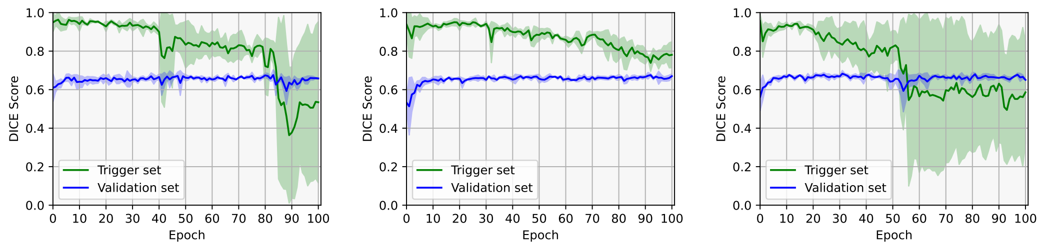
Simple watermark: logo Detailed results on FTAL experiments with constant trigger are reported in Figure 18.



(1) TR = 0.05 (2) TR = 0.15 (3) TR = 0.25

Figure 18: DICE scores of the watermark detectability and model accuracy when retrained with constant trigger with various trigger ratios.

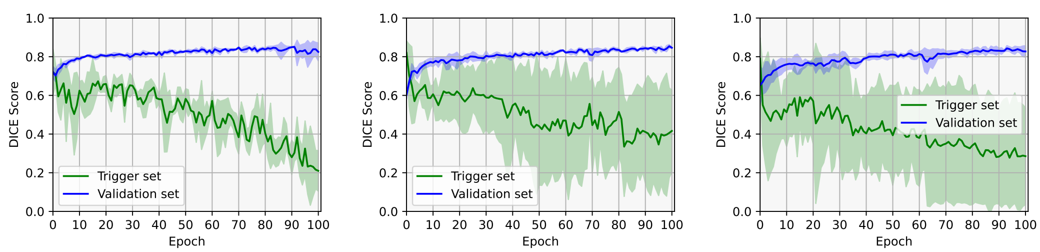
Detailed results on FTAL experiments with dynamic trigger are reported in Figure 19.



(1) TR = 0.05 (2) TR = 0.15 (3) TR = 0.25

Figure 19: DICE scores of the watermark detectability and model accuracy when retrained with dynamic trigger with various trigger ratios.

Geometric watermark Detailed results on FTAL experiments with constant trigger are reported in Figure 20.



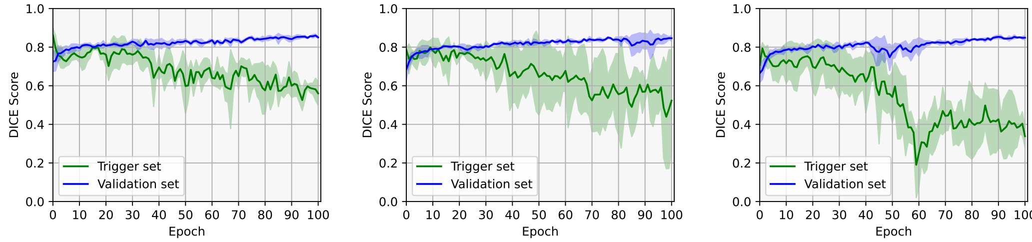
(1) TR = 0.05 (2) TR = 0.15 (3) TR = 0.25

Figure 20: DICE scores of the watermark detectability and model accuracy when retrained with constant trigger with various trigger ratios.

FTAL with dynamic trigger Detailed results on FTAL experiments with dynamic trigger are reported in Figure 21.

A.3 Fine-tuning with Different Learning Rates

All LR values are written in python format (for instance $1e-4 = 0.0001$).

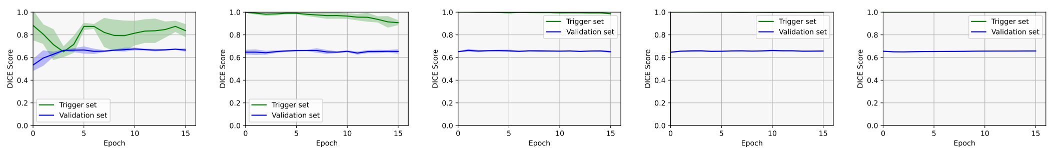


(1) TR = 0.05 (2) TR = 0.15 (3) TR = 0.25

Figure 21: DICE scores of the watermark detectability and model accuracy when retrained with dynamic trigger with various trigger ratios.

A.3.1 FTAL

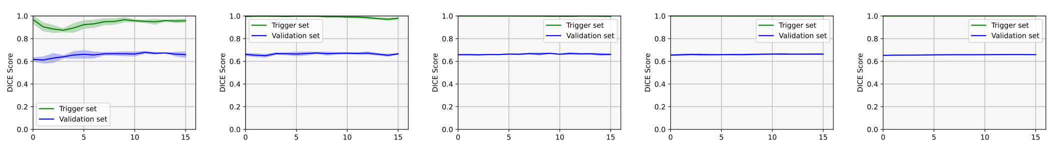
Complex watermark Detailed results on Learning Rate experiments for the *Complex watermark* are reported in Figure 22.



(1) LR = $1e-4$ (2) LR = $0.5e-4$ (3) LR = $1e-5$ (4) LR = $0.5e-5$ (5) LR = $1e-6$

Figure 22: DICE scores of the watermark detectability and model accuracy for FTAL with various learning rates.

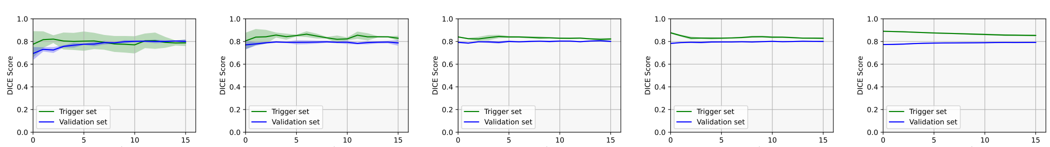
Simple watermark Detailed results on Learning Rate experiments for the *Simple watermark* are reported in Figure 23.



(1) LR = $1e-4$ (2) LR = $0.5e-4$ (3) LR = $1e-5$ (4) LR = $0.5e-5$ (5) LR = $1e-6$

Figure 23: DICE scores of the watermark detectability and model accuracy for FTAL with various learning rates.

Geometric watermark Detailed results on Learning Rate experiments for the *Geometric watermark* are reported in Figure 24.



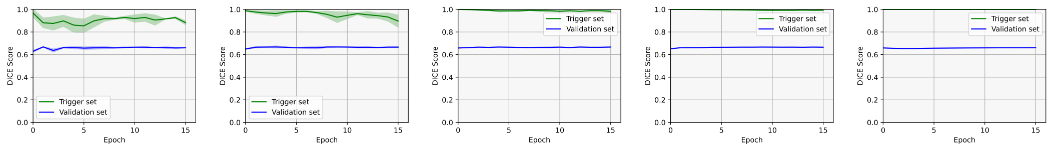
(1) LR = $1e-4$ (2) LR = $0.5e-4$ (3) LR = $1e-5$ (4) LR = $0.5e-5$ (5) LR = $1e-6$

Figure 24: DICE scores of the watermark detectability and model accuracy for FTAL with various learning rates.

A.3.2 FTLL

The following experiments have been made on models trained with the dynamic trigger technique.

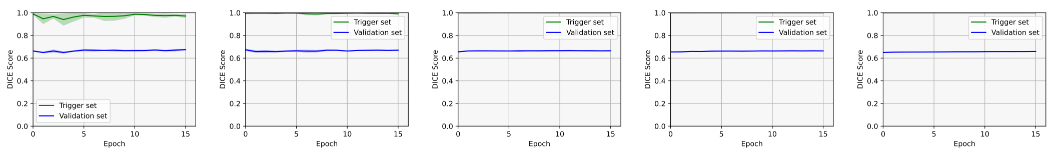
Complex watermark Detailed results on Learning Rate experiments for the *Complex watermark* are reported in Figure 25.



(1) LR = $1e-4$ (2) LR = $0.5e-4$ (3) LR = $1e-5$ (4) LR = $0.5e-5$ (5) LR = $1e-6$

Figure 25: DICE scores of the watermark detectability and model accuracy for FTLL with various learning rates.

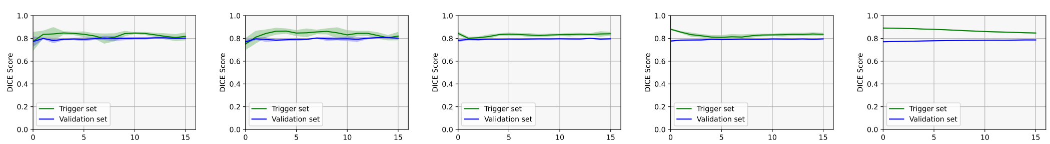
Simple watermark Detailed results on Learning Rate experiments for the *Simple watermark* are reported in Figure 26.



(1) LR = $1e-4$ (2) LR = $0.5e-4$ (3) LR = $1e-5$ (4) LR = $0.5e-5$ (5) LR = $1e-6$

Figure 26: DICE scores of the watermark detectability and model accuracy for FTLL with various learning rates.

Geometric watermark Detailed results on Learning Rate experiments for the *Geometric watermark* are reported in Figure 27.



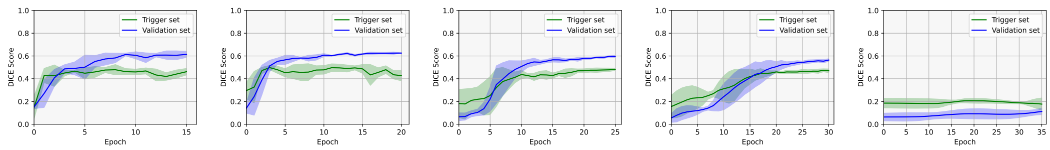
(1) LR = $1e-4$ (2) LR = $0.5e-4$ (3) LR = $1e-5$ (4) LR = $0.5e-5$ (5) LR = $1e-6$

Figure 27: DICE scores of the watermark detectability and model accuracy for FTLL with various learning rates.

A.3.3 RTAL

The following experiments have been made on models trained with the dynamic trigger technique.

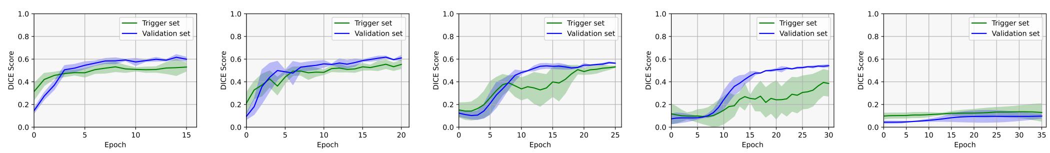
Complex watermark Detailed results on Learning Rate experiments for the *Complex watermark* are reported in Figure 28.



(1) LR = $1e-4$ (2) LR = $0.5e-4$ (3) LR = $1e-5$ (4) LR = $0.5e-5$ (5) LR = $1e-6$

Figure 28: DICE scores of the watermark detectability and model accuracy for RTAL with various learning rates.

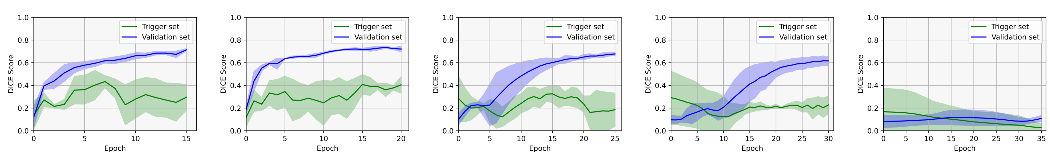
Simple watermark Detailed results on Learning Rate experiments for the *Simple watermark* are reported in Figure 29.



(1) LR = $1e-4$ (2) LR = $0.5e-4$ (3) LR = $1e-5$ (4) LR = $0.5e-5$ (5) LR = $1e-6$

Figure 29: DICE scores of the watermark detectability and model accuracy for RTAL with various learning rates.

Geometric watermark Detailed results on Learning Rate experiments for the *Geometric watermark* are reported in Figure 30.



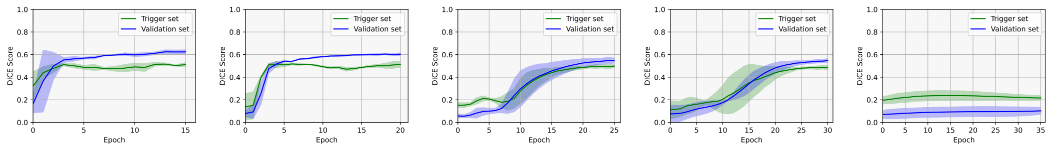
(1) LR = $1e-4$ (2) LR = $0.5e-4$ (3) LR = $1e-5$ (4) LR = $0.5e-5$ (5) LR = $1e-6$

Figure 30: DICE scores of the watermark detectability and model accuracy for RTAL with various learning rates.

A.3.4 RTLL

The following experiments have been made on models trained with the dynamic trigger technique.

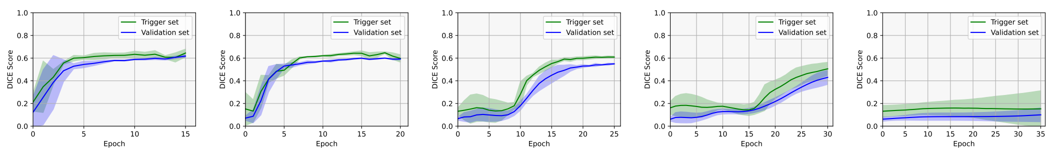
Complex watermark Detailed results on Learning Rate experiments for the *Complex watermark* are reported in Figure 31.



(1) LR = $1e-4$ (2) LR = $0.5e-4$ (3) LR = $1e-5$ (4) LR = $0.5e-5$ (5) LR = $1e-6$

Figure 31: DICE scores of the watermark detectability and model accuracy for RTLL with various learning rates.

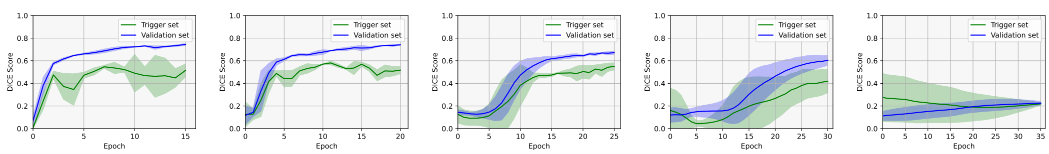
Simple watermark Detailed results on Learning Rate experiments for the *Simple watermark* are reported in Figure 32.



(1) LR = $1e-4$ (2) LR = $0.5e-4$ (3) LR = $1e-5$ (4) LR = $0.5e-5$ (5) LR = $1e-6$

Figure 32: DICE scores of the watermark detectability and model accuracy for RTLL with various learning rates.

Geometric watermark Detailed results on Learning Rate experiments for the *Geometric watermark* are reported in Figure 33.



(1) LR = $1e-4$ (2) LR = $0.5e-4$ (3) LR = $1e-5$ (4) LR = $0.5e-5$ (5) LR = $1e-6$

Figure 33: DICE scores of the watermark detectability and model accuracy for RTLL with various learning rates.