Customized Watermarking for Deep Neural Networks via Label Distribution Perturbation

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ABSTRACT
With the increasing application value of machine learning, the intellectual property (IP) rights of deep neural networks (DNN) are getting more and more attention. With our analysis, most of the existing DNN watermarking methods can resist fine-tuning and pruning attack, but distillation attack. To address these problem, we propose a new DNN watermarking framework, Unified Soft-label Perturbation (USP), having a detector paired with the model to be watermarked, and Customized Soft-label Perturbation (CSP), embedding watermark via adding perturbation into the model output probability distribution. Experimental results show that our methods can resist all watermark removal attacks and outperform in distillation attack. Besides, we also have an excellent trade-off between the main task and watermarking that achieving 98.68% watermark accuracy while only affecting the main task accuracy by 0.59%.

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1 INTRODUCTION
Deep neural network (DNN) technology has achieved great success in many fields in recent years, which brings huge commercial value. Therefore, a well-trained model can be regarded as a kind of intellectual property (IP). Thus, the watermarking mechanism has been applied to DNN as a means of protecting IP rights. By adding a watermark to the model, the model owner can track the model he or she owns through the watermark and prove the ownership by verifying.

The DNN watermarking algorithm has been studied and proposed since around 2017 [1, 4, 10–13]. They mainly embedded watermarks by backdooring through a specific data set, or add designated regularizers to embed watermarks into model parameters. These studies had listed two common and basic requirements that a watermarking algorithm should have: i) Functionality-Preserving: the watermark embedding should not impact the performance of the model too much. ii) Robustness against Removal Attacks: after the model undergoes watermark removal attacks, the watermark should still be well preserved in the model.

Most of existing DNN watermarking methods [1, 4, 10–13] used Fine-tuning attack and Pruning attack as removal attack. However, Knowledge Distillation (KD) [6] should also be regarded as a kind of removal attack. Through KD, an adversary could replicate a model having comparable performance, without directly copying the watermarked model parameters. Nevertheless, most of the recent approaches also had not studied and demonstrated how robust they are to this kind of attack.

Therefore, to gain a better understanding of the robustness of existing DNN watermarking methods against attacks in different settings, we conduct preliminary analysis in Section 4. We found that the performance of watermarking of many methods will decrease when fine-tuning with higher learning rate or pruning with re-training. In addition, most of the approaches cannot resist distillation attack.

To address the issues above, we propose a new customized DNN watermarking approach which is not only robust to common removal attacks (fine-tuning and pruning) but to distillation attack. Inspired by the fact that the student model imitates the output behavior of the teacher model in knowledge distillation, we proposed Unified Soft-label Perturbation (USP) and Customized Soft-label Perturbation (CSP) to embed the watermark into the output via perturbing the prediction probability distribution. The application scenario of USP is when training a self-use model for internal use, we can use USP to detect whether the model has been maliciously changed. For CSP, we add a custom bit string vector to the prediction probability to cause the perturbation on the model prediction and achieve the effect of customization. When the application scenario is we train a model and are going to authorize others to use the model, we can use CSP to protect IP by customizing the watermark for each user.

We design a training framework having a detector paired with the model to be watermarked. The detector is a 5-layer Multi-Layer Perceptron (MLP). During the training process, the detector learns to recognize the features of the prediction probability distribution of the model. After finish training, the owner then can use the detector to trace the model.

To our best knowledge, this is the first work that simultaneously researches defense against three types of attacks and also takes account of the tougher experimental setup of attacks. We evaluate the proposed approach with ResNet18 on multiple benchmark datasets, including CIFAR-5\textsuperscript{1}, CIFAR-10, CIFAR-100, and Tiny Image Net. Experimental results show our proposed approach not only successfully resists all kinds of removal attack, but also has better

\textsuperscript{1}A subset of CIFAR-10 that consists of data with label 0 to 4 in CIFAR-10.
robustness in all different attack settings compared to other state-of-the-art baselines, especially in distillation attack. Besides, our methods also have excellent trade-off between the main task and watermarking compared to other baselines and has great functionality-preserving.

The contributions are summarized as follows.

- We propose a novel deep neural network watermarking framework, Unified Soft-label Perturbation (USP), which not only can resist common watermark removal attacks, but also is robust to distillation attack.
- We further propose Customized Soft-label Perturbation (CSP) to embed customizable watermark by adding specific perturbations to model prediction probability distributions.
- Experimental results on multiple benchmark datasets show that our approach can be generalized to datasets with different numbers of labels and has good customization ability.
- Experimental results compared with other baselines demonstrates that our approach has the best trade-off between the main task and watermarking. Besides, even under difficult attack settings, our approach still has the best robustness.
- Experimental results also indicate our approach has great watermarking performance stability under different attacks. It does not suffer from the sudden drop in signal strength that the signal-based method may encounter.

2 RELATED WORKS

Existing deep neural network (DNN) watermarking approaches can be mainly categorized into three types: i) feature-based methods, ii) trigger-set-based methods and iii) signal-based methods.

Feature-based. This type of methods embed designated pattern, such as binary bit string or vector, into the DNN parameters as watermark. Uchida et al. [10] embeds watermark by adding a new regularization terms. Fan et al. [4] and Zhang et al. [12] use passport-layers to carry the watermarks. RIGA [11] embeds the watermark in the parameters of model, and extract it with a trained DNN.

Trigger-set-based. Trigger-set is a kind of adversarial training samples with specific labels, and the trigger-set-based methods rely on these samples to embed watermarks into DNN. WNN proposed by Adi et al. [1] and the embedding framework proposed by Zhang et al. [13] both include the trigger-set as watermarks into the training data.

Signal-based. The signal-based methods inject signal into the model output as watermark. Charette, Chu et al. [2] designed CosWM which embeds cosine signal into the output of the watermarked model. However, CosWM needs to calculate linear projections, periodic signal function, and power spectrum when embedding and extracting watermark, which is more time-consuming and complicated for users. Moreover, on their paper, only performed CosWM on half of the CIFAR-10 dataset and did not experiment with defense against fine-tuning and pruning attacks.

In addition to the above methods embedding watermark information into models, there are also some researches designing watermarking mechanisms through APIs, such as PRADA [7], Fingerprinting [8], and DAWN [9]. However, API methods is not defensive enough. Since the model itself has no watermark, once someone has a way to obtain the model, it will be directly stolen without any protection.

3 PROBLEM DEFINITION

Neural network watermarking. Watermarking is a method used to protect intellectual property, providing the owner with the ability to claim the ownership. Neural network models are often over-parameterized, and this property can be exploited to embed the information we want other than the main task. A neural network watermarking scheme basically consists two main steps: i) Embedding and ii) Verification. Let M and k denote the model to be trained and the information to be embed. Then we can have

\[ M_{wm} = \text{Embed}(M, k), \]

where \( M_{wm} \) is the embedded model. Let \( M_0 \) denotes the model to be verified, and \( V_{wm} \) denotes the return value of the verify step. In the verification step, usually calculate how accurately \( k \) can be extracted from the model \( M_0 \) or how well it matches the particular behaviors when \( M_0 \) triggered by the trigger-set. Then this step can be written as

\[ V_{wm} = \text{Verify}(M_0, k), \]

and the higher the value of \( V_{wm} \) is, the better the detection of the presence of watermark information \( k \).

Fine-tuning Attack. The adversaries fine-tune the embedded model \( M_{wm} \), attempting to erase the embedded watermark information by updating the parameters with their own dataset \( D_a \). Most of the watermarking methods claim that they are robust to this kind of attack. However, REFIT [3] pointed out that some methods can resist the fine-tuning attack only when the learning rate is small.

Pruning Attack. Pruning is a post-processing operation of neural network. It removes some connections between neurons to reduce the number of parameters. By pruning, the adversaries may remove some parameters carried watermark information, thus erasing the watermark in \( M_{wm} \).

Distillation Attack. Knowledge distillation [6] is one of the model compression methods. For each input, the technique makes the student model imitate the output behavior of the teacher model as closely as possible to learn better than it does on its own. Through distillation, the adversaries can replicate a high-performance new model with their own dataset \( D_a \) without accessing parameters of \( M_{wm} \). Thus, the adversaries will not obtain the parameters carrying the watermark information nor learn any special behavior.

Problem definition. Table 1 summaries the robustness of different neural network watermarking methods to different attacks from our preliminary analysis in Section 4. From Table 1, we can find that the existing methods cannot resist the above three attacks well at the same time. Thus, our task is to design a robust watermarking method against not only fine-tuning and pruning but knowledge distillation, making the watermark still exist in the replicated model after attacked by the adversary. Besides, there are some requirements need to met:

- **Functionality-Preserving**: The impact of watermark embedding on the performance of the main task needs to be as less as possible.
- **Identification Criteria**: the criteria for success in identifying or extracting watermarks should be clear to prevent disputes. For example, \( V_{wm} \), the return value of the verify
Table 1: Robustness of neural network watermarking methods to different attacks. The mark ✓ means the watermarking method is robust to the attack, the mark ✗ means the watermarking method can resist the attack, and the mark Δ means the watermarking method under this attack is not very good but acceptable, or cannot resist under some attack settings.

| Method         | Fine-tuning | Pruning | Re-training | Distillation |
|----------------|-------------|---------|-------------|--------------|
| WNN (USENIX'2018) | ✓           | ✓       | ✗           | ✗            |
| DeepIPR (NIPS’2019) | ✗           | ✓       | ✓           | ✗            |
| PA (NIPS'2020)   | ✓           | ✗       | ✓           | ✗            |
| RIGA (WWW’2021)  | ✓           | ✓       | ✗           | ✓            |
| DAWN (MM’2021)   | ✓           | ✓       | ✗           | ✓            |
| CosWM (AAAI’2022)| ✓           | x       | ✓           | ✓            |

Table 2: Functionality-preserving of different neural network watermarking methods on CIFAR-10

| Method         | Clean main acc.(%) | Watermarked main acc.(%) | wm acc.(%) |
|----------------|---------------------|--------------------------|-----------|
| WNN (USENIX’2018) | 90.67 (-4.63)       | 100.00                   |           |
| DeepIPR (NIPS’2019) | 92.11 (-3.19)       | 100.00                   |           |
| PA (NIPS'2020)   | 94.02 (-1.27)       | 100.00                   |           |
| RIGA (WWW’2021)  | 94.43 (-0.87)       | 100.00                   |           |
| DAWN (MM’2021)   | 79.27 (-26.1)       | 88.80                    |           |
| CosWM (AAAI’2022)| 95.14               | 88.28                    |           |

4 PRELIMINARY ANALYSIS

In this section, we conduct preliminary analyses with recent watermarking approaches to know their performance and robustness under different settings of removal attacks. For each approach, we generate a watermarked ResNet18 model on CIFAR-10 with their method respectively. Each watermarked model is trained with 160 training epochs and has a learning rate starting as 0.1.

Functionality-Preserving. Table 2 shows the ability of functionality-preserving of each watermarking method. It can be found that most methods achieve good results on main task accuracy and watermark accuracy. The trigger-set-based method, WNN, has relatively poor functional-preserving. Because trigger-set-based methods would combine trigger set into the main task training set, data not relevant to the main task may affect the performance of the model in the main task. Besides, the overall performance of DAWN is significantly lower. The reason should be that the way DAWN generates trigger-set is to directly modify the labels of some data in the main task dataset, so that the features of trigger-set will be similar to the features of main task dataset but having different labels.

Fine-tuning Attack. Table 3 shows the robustness to fine-tuning attacks with different learning rate settings of each watermarking method. We fine-tune the watermarked models for 100 epochs with small learning rate, 0.001 and larger learning rate, 0.01 on the same CIFAR-10 training set. The watermark accuracy of DAWN is decreased since the same reason mentioned above: the trigger-set is generated from the main task dataset. Thus, after fine-tuning, the effect caused by the trigger-set on the main accuracy is decreased, and watermark accuracy drops dramatically. Then we look at the results under the attack with a larger learning rate. It can be found that the watermark embedded in almost all methods are obviously damaged.

Pruning Attack. Table 3 shows the robustness to pruning attacks with and without re-training of each watermarking method. We adopt the classic pruning method [5] proposed and show the results after pruning off 80% parameters. However, after re-training 100 epochs with a learning rate of 0.01, we can find the watermark accuracy of most methods drop obviously but their main task accuracy recovers with re-training.

Distillation Attack. Table 3 shows the robustness in distillation attack of each watermarking method. We distill the watermarked model with the same CIFAR-10 dataset, and set ResNet18 as student model, training epochs as 160, learning rate as 0.1, and distillation temperature as 4. We can see that except for the signal-based method, CosWM, and API method, DAWN, the watermarks of all the other methods cannot be well preserved on the distilled student model. Because knowledge distillation attack can replicate the model with just the main task related dataset and without accessing parameters of the watermarked model. Thus, the student model will not obtain the parameters carrying the watermark information embedded by featured based methods nor learn any special behavior of trigger-set-based methods.

From our preliminary analysis, we can observe two things:

- First of all, most of the existing watermarking methods can not resist to tougher removal attack setting, such as fine-tuning with larger learning rate and re-training after pruning.
- Secondary, most of the watermarks embedded by existing watermarking methods will disappear after being attacked by knowledge distillation.

5 ALGORITHM DESIGN

Most of the existing watermarking methods can not defend against knowledge distillation attack. In order to address this problem, we design a watermarking framework to hide watermarks in the prediction probabilities to resist the imitation behavior in knowledge distillation.

5.1 Unified Soft-label Perturbation (USP)

The basic idea of USP is to add some perturbation as a watermark to the output of the model during the training process, making the
prediction probability distribution of the trained model different from general models. In addition, we design a detector model to detect the differences in the outputs to identify the watermarked model. If someone intends to steal the trained model by knowledge distillation, the perturbation effects will also be transferred to the model replicated, because the student model would learn the output behavior of the teacher model.

Figure 1: The flow of Unified Soft-label Perturbation (USP).

The flow is shown in Figure 1. There are two main steps: i) adversary pretraining and ii) watermark embedding and detector training. First, in step i, without adding any perturbation, we train a normal model \( M_n \) to be an adversary in the next step. The role of the pre-trained model \( M_n \) in step ii is to help train the detector to distinguish the difference between the watermarked model and the normal model.

In step ii, we designed a training method to train the model \( M_{wm} \) to be watermarked and the corresponding detector \( M_d \). To train a model having special prediction probability distribution, we apply the KL divergence loss function with soft temperature \( T \), similar to knowledge distillation, to calculate the difference between the outputs of it and the adversary model \( M_n \), the normal model trained

\[
\mathcal{L}_{KLD} = T^2 \cdot KL(\text{softmax}(O_m/T), \text{softmax}(O_{wm}/T)),
\]

where \( O_{wm} \) and \( O_m \) are respectively the output of \( M_{wm} \) and the output of \( M_n \). The purpose of using a loss function similar to knowledge distillation is to hope that when an adversary tries to distill the model, the perturbations in the model output can be more easily learned by the student model.

Afterwards, we add the KL divergence loss with a negative coefficient \( \alpha \) to the main task loss calculated by cross-entropy to get the total model loss \( \mathcal{L}_{Model} \) which is defined as follows.

\[
\mathcal{L}_{Model} = \alpha \cdot \mathcal{L}_{KLD} + \mathcal{L}_{MainTask} + \mathcal{L}_{Detect}.
\]

\[
\mathcal{L}_{Detect} = CrossEntropy(O_{wm}, Y),
\]

where \( Y \) is the ground-truth label. The negative coefficient \( \alpha \) allows model \( M_{wm} \) to increase the difference from the adversary \( M_{normal} \) as much as possible, thus promoting it to have different prediction probability distributions.

The detector model is also trained when training the model. We design a five-layer MLP as the detector, and take the output of \( M_{wm} \) and \( M_n \) as its input to perform the binary classification task of identifying watermarks. In each epoch, the main task data \( X \) will be input into \( M_{wm} \) and \( M_n \) at the same time, generating the prediction outputs \( o_{wm}^i \) and \( o_n^i \). For each \( o_{wm}^i \), we assign label \( \hat{o}_{wm}^i = 1 \), likewise, for each \( o_n^i \), we assign label \( \hat{o}_n^i = 0 \).

\[
\text{Label}(o_m^i) = \begin{cases} 
\hat{o}_{wm}^i = 1 & \text{if } m \text{ is } M_{wm}, \\
\hat{o}_n^i = 0 & \text{if } m \text{ is } M_n.
\end{cases}
\]

Then we can have detector training dataset \( D_d = (X_d, Y_d) \), where \( X_d = \{O_{wm}, O_n\} \) is the input and \( Y_d = \{\hat{o}_{wm}, \hat{o}_n\} \) is the label. After preparing the dataset, the binary classification training of the detector can be performed. For this task, we use binary cross-entropy to calculate the detecting loss \( \mathcal{L}_{Detect} \). Besides, to reduce additional computational cost, we set an early stopping mechanism for the detector training process, which ends the detector training once the detecting accuracy reaches 100.

\[
\mathcal{L}_{Detect} = \text{BinaryCrossEntropy}(M_d(X_d), Y_d).
\]

After updating the detector model \( M_d \) with \( \mathcal{L}_{Detect} \), we add \( \mathcal{L}_{Detect} \) to the model loss \( \mathcal{L}_{Model} \) to get a total loss \( \mathcal{L}_{Total} \) for updating \( M_{wm} \). In this way, \( M_{wm} \) will also take into account the

Table 3: Robustness to removal attacks of different watermarking methods on CIFAR-10. The main (%) indicates main task accuracy and the wm (%) indicates watermark accuracy.

| Method          | Before Attack | Fine-tune (lr = 0.001) | Fine-tune (lr = 0.01) | Prune | Re-train after Prune | Distill |
|-----------------|---------------|------------------------|-----------------------|--------|----------------------|---------|
|                 | main (%)      | wm (%)                 | main (%)              | wm (%) | main (%)              | wm (%)  |
| WNN (USENIX’18)| 90.67         | 100.00                 | 90.72                 | 100.00 | 92.43                 | 52.31   |
| DeepIPR (NIPS’19)| 92.11       | 100.00                 | 92.40                 | 100.00 | 92.55                 | 70.48   |
| PA (NIPS’20)   | 94.02         | 100.00                 | 94.07                 | 100.00 | 92.26                 | 70.73   |
| RIGA (WWW’21) | 94.43         | 100.00                 | 94.97                 | 100.00 | 93.34                 | 12.80   |
| DAWN (MM’21)  | 79.27         | 88.80                  | 80.53                 | 8.80   | 80.34                 | 0.00    |
| CosWM (AAAI’22)| 95.14         | 88.28                  | 94.95                 | 88.35  | 95.00                 | 52.45   |

\[\]
discriminative ability of the detector when updating. We define $L_{Total}$ as follows.

$$L_{Total} = L_{Model} + \beta \cdot L_{Detect},$$  \hspace{1cm} (6)

where $\beta$ is the coefficient to moderate the influence of the detector. Then, we finally obtain the watermarked model trained by USP. When the model owner train a self-used model, USP can protect the IP of the model well from not only fine-tuning attack and pruning attack, but distillation attack, and can also be used to detect whether the model has been maliciously changed since the watermark in the model is related to performance the model.

Table 4: Result of three different watermarked model and detector pairs generated by USP on CIFAR-10.

| M_{wm1} | M_{wm2} | M_{wm3} |
|---------|---------|---------|
| Main task acc. of Unwatermarked Model (%) | 95.30 | 94.10 | 93.00 |
| Main task acc. of $M_{wm}$ (%) | 94.10 | 93.00 | 93.46 |
| Identified by $M_{d1}$ (%) | 99.74 | 93.91 | 87.81 |
| Identified by $M_{d2}$ (%) | 99.87 | 97.56 | 91.14 |
| Identified by $M_{d3}$ (%) | 99.91 | 98.88 | 99.57 |

However, if there is a need for customizing, USP is defective: the detector is not sensitive enough to identify the custom characteristics of different watermarks. There are the results of three different watermarked model and detector pairs generated by the USP method in Table 4. From Table 4, we can find although the detector can well detect whether a model is watermarked, it can not correctly distinguish whether the model has someone’s watermark. We think the reason is that only using KL divergence loss cannot constrain the form of the perturbation well, which may cause the model just randomly changes the probability distribution to reduce the total loss, making the characteristics of the output distribution inconsistent. Thus, the detector can only distinguish the difference from the normal model, instead of the specific watermark features. To improve the deficiency, we design Customized Soft-label Perturbation (CSP).

5.2 Customized Soft-label Perturbation (CSP)

When we train a model and are going to authorize others to use the model, we can use CSP to protect IP. We customize the watermark for each user, and if there is an authorized model breached by a user, we can use CSP to verify the watermark, prove our ownership and find the person who breached the model.

The flow is shown in Figure 2 which having three steps: i) adversary pretraining, ii) watermark embedding and detector training, and iii) overall fine-tuning. In the first step, CSP also trains an ordinary model $M_n$ to become the adversary in the next step. While in the watermark embedding and detector training step, CSP has some adjustment. We first introduce some terms. We define a vector $S \in \{0, 1, -1\}$ as the watermark signal, where $l$ is the length of $S$, and $\gamma$ as a signal strength factor. In order to solve the problem of insufficient customization ability of the USP method, we try to make the output probability distribution of $M_{wm}$ have consistent features. We adjust and constrain $O_{wm}$ to be $\tilde{O}_{wm}$ with $S$ and $\gamma$ as follows.

$$\tilde{o}_{wm}^i = o_{wm}^i - \gamma \cdot S,$$  \hspace{1cm} (7)

where $O_{wm} = \{o_{wm}^0, \cdots, o_{wm}^n\}$ and $n$ is the number of training data. We preset the length of the watermark, $l$, to be the same as the number of classes of the main task dataset. For example, when using CIFAR-10 as the main task dataset, the length of the $S$ will be set to 10. The factor $\gamma$ is used to moderate the signal strength literally. The strength of the signal will increase as the factor is increased.

However, when embedding watermarks on a task with many labels, if the length of the $S$ is the same as the number of labels, it will be more complicated to assign. In this case, just filter out part of the labels to carry the watermark, then the length of $S$ can be reduced. For example, on CIFAR-100 task, we just using label 0 to label 9 for embedding as follows.
We replace the result calculated by the USP framework in Eq.2. We just need to modify Eq.3 slightly to obtain a new main task loss function for this framework.

\[
\hat{y}_{wm}[j] = \begin{cases} 
  \hat{o}_{wm}^j \cdot y \cdot S[k] & \text{if } \text{dict}[j] = k, \\
  \hat{o}_{wm}^j & \text{else,}
\end{cases}
\]

where \( \text{dict} \) is the dictionary to filter the labels, and \( \text{dict}[j] = k \) means label \( j \) is the \( k \)-th one be filtered out to embed watermark.

Basically, the composition of the model loss function \( L_{Model} \) is as same as that of the USP framework in Eq.2. After updating the detector model, we assign labels in the same way as the USP method in Eq.4, but modify how the detector training data be generated. Here, we use \( \log \text{softmax} \) to modify \( O_{wm} \) and \( \hat{O} \), to \( \hat{O}_{wm} \) and \( \hat{O} \).

\[
\hat{O}_{wm} = \log \text{softmax}(O_{wm}) \\
\hat{O} = \log \text{softmax}(O_{wm})
\]

We hope the detector can learn the features of the watermark signal we embed according to the bias on the probability distribution. Therefore, we adopt the \( \log \text{softmax} \) function that takes the \( \log \) of the result calculated by \( \text{softmax} \). \( \text{softmax} \) can convert the output into the form of probability we want, and taking the \( \log \) value of the result makes the gap between each probability more obvious.

The detector training process is as same as the one in the USP. After updating the detector model \( M_d \), we sum the detecting loss \( L_{Detect} \) and the model loss \( L_{Model} \) to obtain the total loss. The total loss \( L_{Total} \) can be defined as follow.

\[
L_{Total} = L_{Model} + \beta \cdot L_{Detect}
\]

In overall fine-tuning step, we fine-tune the watermarking model \( M_{wm} \) and continue to train the detector while fine-tuning in this step. We regard fine-tuning as a data augmentation of detector. Here, we updated \( M_{wm} \) without adding KL loss, and use the original output \( O_{wm} \) without modification. The loss function of fine-tuning \( L_{Finetune} \) is defined as follow.

\[
L_{Finetune} = \text{CrossEntropy}(O_{wm}, Y)
\]

The reason we directly fine-tune \( M_{wm} \) without modifying its output is that in the last stage of training, \( M_{wm} \) will come to a relatively optimal area in the loss function considering signal embedding. We believe that using the original output directly in such cases will allow \( M_{wm} \) to focus more on improving the performance of the main task without causing watermark damage. Moreover, fine-tuning will make the prediction distribution have slight changes that the detector has not seen before, so that the detector then can obtain more training materials to enhance its robustness.

However, in order to prevent the situation where fine-tuning has a significant impact on the watermark, we set up a re-embed mechanism. When the watermark accuracy is lower than the threshold \( \tau \), \( O_{wm} \) will be modified again to deepen the watermark. At last, we summarize the loss function of the overall fine-tuning \( L_{Finetune} \) step as follows:

\[
L_{Finetune} = \begin{cases} 
  \text{CrossEntropy}(O_{wm}, Y) & \text{if } \text{acc}_{wm} > \tau, \\
  \text{CrossEntropy}(\hat{O}_{wm}, Y) & \text{else.}
\end{cases}
\]
6.2 Experiment Setting.

**Baselines.** For fair comparisons, we train a ResNet18 on CIFAR-10 with the same training epochs, starting learning rate, and batch size for each baseline method as possible. We set training epochs as 160 and starting learning rate as 0.1.

**USP.** We train ResNet18 on CIFAR-10 with 160 training epochs, 0.1 starting learning rate.

**CSP.** We train ResNet18 on four datasets. On CIFAR-5 and CIFAR-10, we set training epochs as 120 and fine-tuning epochs as 120. The learning rate starts from 0.1 and decreases by timing 0.1 in epoch 80, 120. On CIFAR-100 and Tiny ImageNet, we set training epochs as 150 and fine-tuning epochs as 120. The learning rate of CIFAR-100 task starts from 0.1 and decreases by timing 0.2 in epoch 60, 120 and 150. The learning rate of Tiny ImageNet task starts from 0.001 and decreases by timing 0.2 in epoch 60, 120 and 160. The architecture of detector is a 5-layer MLP. The detector optimizer is Adam, and the starting learning rate is 0.008. Besides, only when the watermark accuracy is greater than 85%, we consider the watermark detection successful.

6.3 Terms and performance metrics.

We evaluate the approaches with the following metrics. **main acc.** indicates the accuracy on the main task. **wm acc.** indicates the accuracy of the detector detecting the outputs from the watermarked and unwatermarked model. The higher the value indicates the better the detector can identify whether there is a watermark in the outputs. If there is x testing image, we will have 2x balanced detection testing data, of which there are x watermarked data and x unwatermarked data each. For example, CIFAR-10 has 10,000 testing images, we will obtain 20,000 testing detection testing data, of which there are 10,000 watermarked data and 10,000 unwatermarked data.

For WNN and DAWN, **wm acc.** indicates the accuracy of the trigger set. The higher the value, the better the classification result of the trigger set, that is, the better the watermark identification effect.

For DeepIPR, PA, and RIGA, **wm acc.** indicates the bit-correct-rate of the embedded signature bit-strings. A higher value indicates the signature can be identified better.

**wm det rate.** indicates the rate of watermark detected by the detector in the outputs of a model. The higher **wm det rate.** the higher confidence of the detector in recognizing the the model. **cmps ratio.** indicates compression ratio, the ratio of the number of parameters of the student model and the teacher model, i.e., the ratio of the student model size to the teacher model size.

For **CosWM**, **wm acc.** indicates the signal-noise-ratio of the embedded signal. A higher value indicates stronger signal. **wm det rate.** indicates the rate of watermark detected by the detector in the outputs of a model. The higher **wm det rate.** the higher confidence of the detector in recognizing the the model. **cmps ratio.** indicates compression ratio, the ratio of the number of parameters of the student model and the teacher model, i.e., the ratio of the student model size to the teacher model size.

6.4 Overview

We compare the robustness of our proposed approaches with the baselines in Table 5. Here we obtain the watermarked ResNet18 models on CIFAR-10 with each watermarking method, and apply removal attacks with tougher settings, which make most watermarking methods less effective in the preliminary analysis experiments, to them.

**6.4.1 Functionality Preservation.** First of all, we evaluate the functionality-preserving ability of each method. From the experimental results in Table 5, our proposed approaches have great functionality-preserving ability which only have 1.55% and 0.59% drops respectively on the main task accuracy. Compared to other baselines, our proposed approaches have outstanding trade-off between the main task and watermarking.

**6.4.2 Fine-tuning attack.** For fine-tuning attack, we adopt larger learning rate, 0.01, to fine-tune the watermarked models for 100 epochs. We take the result with the highest main acc. From the experimental results, most methods have obviously drop in watermark accuracy, but maintain well or even improve in main task accuracy. In contrast, the watermark accuracy of ours and CosWM is only a little affected.

**6.4.3 Pruning attack without re-training.** For pruning experiment, we prune 80 % weights off without re-training, and the results are shown in Table 5. From the results, Dawn and CosWM have significant drop on both the main task accuracy and watermark accuracy after pruning, while our methods can still maintain high watermarking accuracy. It can be seen that in pruning attack without re-training, our methods have better robustness.
6.4.4 Pruning attack with re-training. In this experiment, we also prune 80% weights off and set the re-training epochs as 100 and the learning rate as 0.01. We take the result with the highest main acc. Though the watermarking accuracy of WNN, Deep-IPR, and PA only have little drop after pruning, their watermarking effect becomes poor after re-training. Moreover, while both the main task accuracy and water mark accuracy of CosWM recover after re-training, the watermark accuracy is much lower then it used to be. Although our methods have a little drop in watermark accuracy, they still maintain high identification ability after re-training.

6.4.5 Distillation attack. We distill the watermarked model to a ResNet18 student model on CIFAR-10 for 160 epoch and set the learning rate as 0.1 and the distillation temperature as 4. We have known that all baselines except signal-based methods are incapable of resisting distillation attacks from the preliminary analysis. However, Table 5 shows that our proposed methods can successfully resist to distillation attack with great watermark identification effect that have the best watermark accuracy than all baselines.

Table 6: Customization Ability on CIFAR-5. We have 5 different watermarked ResNet18 models on CIFAR-5.

| CIFAR-5   | $M_{wm1}$ | $M_{wm2}$ | $M_{wm3}$ | $M_{wm4}$ | $M_{wm5}$ |
|-----------|-----------|-----------|-----------|-----------|-----------|
| Main task accuracy (%) | 87.87 | 88.05 | 87.12 | 87.77 | 87.44 |
| wm det rate of $M_{d1}$ (%) | 88.56 | 14.90 | 12.21 | 17.30 | 4.86 |
| wm det rate of $M_{d2}$ (%) | 10.48 | 86.17 | 14.34 | 11.64 | 11.63 |
| wm det rate of $M_{d3}$ (%) | 16.15 | 12.36 | 85.06 | 5.88 | 0.72 |
| wm det rate of $M_{d4}$ (%) | 16.47 | 6.76 | 5.88 | 87.52 | 0.41 |
| wm det rate of $M_{d5}$ (%) | 2.15 | 7.62 | 2.17 | 0.61 | 86.53 |

Table 7: Customization Ability on CIFAR-10. We have 5 different watermarked ResNet18 models on CIFAR-10.

| CIFAR-10  | $M_{wm1}$ | $M_{wm2}$ | $M_{wm3}$ | $M_{wm4}$ | $M_{wm5}$ |
|-----------|-----------|-----------|-----------|-----------|-----------|
| Main task accuracy (%) | 94.67 | 94.80 | 94.82 | 94.46 | 94.67 |
| wm det rate of $M_{d1}$ (%) | 96.81 | 24.52 | 7.83 | 0.71 | 3.35 |
| wm det rate of $M_{d2}$ (%) | 18.35 | 98.86 | 0.24 | 2.99 | 0.35 |
| wm det rate of $M_{d3}$ (%) | 0.00 | 0.00 | 90.94 | 0.00 | 14.51 |
| wm det rate of $M_{d4}$ (%) | 0.73 | 3.41 | 0.40 | 98.54 | 0.57 |
| wm det rate of $M_{d5}$ (%) | 1.96 | 2.72 | 10.95 | 0.11 | 90.00 |

6.5 Customization Ability

We train ResNet18 on the CIFAR-5, CIFAR-10, CIFAR-100, and Tiny ImageNet to evaluate the customization ability of our method. For each dataset, we generate 5 sets of watermarked model and detector, use wm det rate as metric. The wm det rate here indicates how confident the detector is in identifying the model.

For CIFAR-5 and CIFAR-10, we set the signal strength factor $\gamma$ as 2 and 5 and set the length of signal vector $S$ to embed as the same number of labels in the respective dataset.

For CIFAR-100, we set the signal strength factor $\gamma$ as 5 and the length of signal vector $S$ to embed as 10.

For Tiny ImageNet, we set the signal strength factor $\gamma$ as 10 and the length of signal vector $S$ to embed as 10.

Table 8: Customization Ability on CIFAR-100. We have 5 different watermarked ResNet18 models on CIFAR-100.

| CIFAR-100 | $M_{wm1}$ | $M_{wm2}$ | $M_{wm3}$ | $M_{wm4}$ | $M_{wm5}$ |
|-----------|-----------|-----------|-----------|-----------|-----------|
| Main task accuracy (%) | 76.67 | 76.27 | 76.06 | 76.17 | 76.46 |
| wm det rate of $M_{d1}$ (%) | 93.13 | 12.46 | 8.39 | 7.05 | 10.11 |
| wm det rate of $M_{d2}$ (%) | 9.77 | 91.59 | 8.53 | 6.32 | 13.77 |
| wm det rate of $M_{d3}$ (%) | 10.24 | 10.12 | 93.53 | 8.92 | 11.34 |
| wm det rate of $M_{d4}$ (%) | 8.14 | 7.44 | 15.32 | 91.22 | 9.53 |
| wm det rate of $M_{d5}$ (%) | 20.56 | 14.58 | 17.99 | 10.83 | 91.60 |

Table 9: Customization Ability on Tiny ImageNet. We have 5 different watermarked ResNet18 models on Tiny ImageNet.

| Tiny ImageNet | $M_{wm1}$ | $M_{wm2}$ | $M_{wm3}$ | $M_{wm4}$ | $M_{wm5}$ |
|---------------|-----------|-----------|-----------|-----------|-----------|
| Main task accuracy (%) | 67.00 | 67.30 | 67.24 | 67.11 | 67.16 |
| wm det rate of $M_{d1}$ (%) | 95.99 | 12.45 | 9.80 | 12.14 | 9.44 |
| wm det rate of $M_{d2}$ (%) | 19.88 | 96.04 | 21.14 | 12.34 | 8.43 |
| wm det rate of $M_{d3}$ (%) | 17.91 | 18.82 | 95.11 | 5.71 | 11.54 |
| wm det rate of $M_{d4}$ (%) | 23.91 | 12.38 | 16.87 | 91.57 | 11.56 |
| wm det rate of $M_{d5}$ (%) | 8.02 | 18.88 | 15.47 | 17.34 | 93.73 |

From Table 6, 7, 8, and 9, we can observe that their values on the diagonal are very high, while the values of other parts are very low, all below 25%, which means that the recognition ability of each detector for its corresponding model is very high, and it will not mistake the model with other watermarks as its own. In addition, the results also indicate that our method has good customization ability regardless of the number of labels in the main task dataset.
Table 10: Distillation Attack with Different cmprs ratio. We adopt 4 different student models, including ResNet18 (11,173,962 parameters), Mobilenet v2 (2,254,090 parameters), Shufflenet v2 (1,268,646 parameters), and PreResNet20 (272,282 parameters).

| Method     | ResNet18 (Teacher) | ResNet18 (Student) | Mobilenet v2 (Student) | Shufflenet v2 (Student) | PreResNet20 (Student) |
|------------|---------------------|--------------------|------------------------|-------------------------|-----------------------|
|            | main acc.(%) | wm acc.(%) | main acc.(%) | wm acc.(%) | main acc.(%) | wm acc.(%) | main acc.(%) | wm acc.(%) | main acc.(%) | wm acc.(%) |
| WNN        | 90.67       | 100.00   | 92.24       | 8.00       | 90.12       | 8.52       | 89.11       | 11.00      | 89.03       | 9.10      |
| DeepIPR    | 92.11       | 100.00   | 90.14       | 0.00       | 91.32       | 0.00       | 90.95       | 0.00       | 90.42       | 0.00      |
| PA         | 94.02       | 100.00   | 92.33       | 0.00       | 92.03       | 0.00       | 90.21       | 0.00       | 90.51       | 0.00      |
| RIGA       | 94.43       | 100.00   | 94.12       | 0.00       | 92.76       | 0.00       | 91.17       | 0.00       | 90.93       | 0.00      |
| DAWN       | 79.17       | 99.60    | 78.11       | 86.20      | 77.31       | 86.19      | 70.54       | 75.34      | 68.54       | 72.47     |
| CosWM      | 95.14       | 88.28    | 95.15       | 83.54      | 92.21       | 83.03      | 92.71       | 84.89      | 92.66       | 83.92     |
| USP (Ours) | 93.75       | 99.56    | 94.92       | 99.27      | 92.06       | 99.08      | 90.91       | 99.34      | 90.22       | 98.26     |
| CSP (Ours) | 94.71       | 98.68    | 90.05       | 91.86      | 92.12       | 96.21      | 92.86       | 94.94      | 92.74       | 92.24     |

Table 11: Customization of different watermarking method on CIFAR-10. Identified rate indicates the average rate that the correct watermark is successfully recognized (true positive). Misidentified rate indicates the average rate that the wrong watermark is misidentified (false positive).

| Identified rate (%) | Misidentified rate (%) |
|---------------------|------------------------|
| WNN (USENIX’2018)  | 100.00                 | 10.34                  |
| DeepIPR (NIPS’2019)| 100.00                 | 6.93                   |
| PA (NIPS’2020)     | 100.00                 | 5.49                   |
| RIGA (WWW’2021)    | 100.00                 | 25.00                  |
| DAWN (MM’2021)     | 88.80                  | 0.00                   |
| CosWM (AAAI’2022)  | 85.57                  | 57.34                  |
| CSP (Ours)         | 99.16                  | 0.97                   |

To see how our customization ability compares to existing methods, we generate a total of 3 watermarking models on CIFAR-10 for each baseline method and use True identified rate and Misidentified rate to evaluate the customization ability of each method. For watermarking methods that need to assign a bit string or a vector as watermark embedding, such as feature-based methods, we set the similarities of the bit strings or vectors of the three watermarked models to each other to be 50%. For CosWM, we set 3 different target class and random unit projection vector for each watermarked model. The experimental results are presented in Table 11. True identified rate represents the rate at which the correct watermark is successfully recognized, for example, wm1 detected from Mwm1, and Misidentified rate represents the rate at which the wrong watermark is misidentified. From Table 11, we can find that DAWN seems to work well on the misidentified rate. Because DAWN directly uses a subset of the main task dataset as the trigger set, the same image will have completely different labels in the training data of different watermarked models. However, DAWN is the worst at recognizing its own watermark. CSP achieves 97% of misidentified rate which is much lower than most of the methods, and it performs well in true identified rate which is as high as 99.16%. The results show that, compared with baselines, CSP achieves a better balance between the self-recognition effect and the probability of misidentification.

6.6 Robustness against Knowledge Distillation Attack with Different Compression Rate

From Table 5, we know most of the watermarking methods cannot resist to knowledge distillation attack, except CosWM and our proposed approach. To better understand the defense power of these watermarking methods against distillation attacks, we adopt 4 different model architectures to be the student models, including ResNet18, Mobilenet v2, Shufflenet v2, and PreResNet20, on CIFAR-10. We set the training(distilling) epochs as 160, learning rate as 0.1, and distillation temperature as 4.

The results are summarized in Table 10. We can find that our methods always achieve the best watermark accuracy. On the student ResNet18 model, our methods have 99.27% and 91.86% watermark accuracy, and on the smallest student model, PreResNet20, our methods also have 98.26% and 92.24% watermark accuracy. It indicates that our methods are robust to distillation attacks that not limited by the model compression size.

7 CONCLUSION

In this paper, we design a deep neural network watermarking framework Unified Soft-label Perturbation (USP), which has a detector paired with the model to be watermarked, to defend against distillation attacks. We further propose Customized Soft-label Perturbation (CSP) to embed the watermark into the output via perturbing the prediction probability distribution. Experiments show that our proposed approaches successfully resist different kinds of watermarking removal attacks, and outperform the other state-of-the-art baselines in tougher attack settings.
We evaluate our method on four different datasets: CIFAR-5, CIFAR-10, CIFAR100, and Tiny ImageNet datasets.

1.4. All the experiments are conducted with Intel (R) Core (TM) i9-9900K CPU @ 3.60GHz, NVIDIA 2080Ti, and Ubuntu 18.04.6.

A DETAILS OF EVALUATION SETUP

A.1 Environments.

We implement our framework, RIGA and CosWM in PyTorch 1.3. For WNN, DeepIPR, PA, and DAWN, we adopt their source code provided on the github. WNN is implemented in PyTorch 0.4.1, DeepIPR and PA are implemented in PyTorch 1.3. DAWN is implemented in PyTorch 1.4. All the experiments are conducted with Intel (R) Core (TM) i9-9900K CPU @ 3.60GHz, NVIDIA 2080Ti, and Ubuntu 18.04.6.

A.2 Datasets.

We evaluate our method on four different datasets: CIFAR-5, CIFAR-10, CIFAR100, and Tiny ImageNet datasets.

CIFAR-10 has 10 labels with 50,000 training and 10,000 testing images. For each label, there are 5,000 training and 1,000 testing images. The resolution of each color image is 32 × 32.

CIFAR-5 is a subset of CIFAR-10 that consists of data with label 0 to 4 in CIFAR-10. Thus, each label has 5,000 training and 1,000 testing images as CIFAR-10, and the resolution of image is also 32 × 32.

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A.3 Experiment Setting.

Our method. We train ResNet18 on four datasets. On CIFAR-5 and CIFAR-10, we set batch size as 512. On CIFAR-10 and Tiny ImageNet, we set batch size as 256. On CIFAR-5 and CIFAR-10, the detector learning rate decreases by timing 0.1 in epoch 140. On CIFAR-100 and Tiny ImageNet, the detector learning rate decreases by timing 0.1 in epoch 160.

Baselines. For CosWM, the learning rate starts from 0.1 and decreases by timing 0.1 in epoch 80, 120. The optimizer is SGD with Nesterov momentum setting momentum as 0.9 and weight decay as 5 × 10−4. For RIGA, we set training epochs as 160 and batch size as 128, adopt Adam as optimizer, and make the learning rate starts from 0.001 and decreases by timing 0.1 in epoch 80, 120.

Table 12: Customization ability of CSP on CIFAR-10.

| # Models | Identified rate (%) | Misidentified rate (%) | F1 score (%) |
|---------|---------------------|------------------------|--------------|
| 3       | 99.168              | 0.977                  | 99.982       |
| 5       | 98.604              | 0.867                  | 99.210       |
| 7       | 98.892              | 11.194                 | 76.142       |
| 10      | 96.114              | 10.510                 | 76.031       |
| 13      | 96.884              | 9.777                  | 76.418       |
| 15      | 95.335              | 8.397                  | 74.005       |
| 17      | 95.058              | 8.507                  | 70.124       |
| 20      | 94.977              | 8.875                  | 69.412       |

H B CUSTOMIZATION ABILITY OF CSP

Then we further evaluate the customization ability of CSP with a larger number of models and the results are in Table 12. We vary the number of models from 3 to 20. We can see from the results that the average misidentified rate will increase as the number of models increases, because the total number of labels in the dataset is fixed. When the number of models increases, the range of disturbances that the watermark needs to add to the output will become larger, making The locations that add perturbations to each other have an increased chance of overlapping, which in turn affects the misidentified rate. Even so, compared with other methods, the average misidentified rate of CSP is still low and seems to converge at around 8% 10%, and the average identified rate and the average remains very high, still more than 94%.
fine-tuning attack and pruning attack with re-training to know the robustness of each model. We vary $\tau$ in [75, 80, 85, 90, 95]. For fine-tuning attack, we fine-tune the models with 100 epochs and a learning rate of 0.01. For pruning attack with re-training, we prune off 80% parameters, setting the re-training epoch and learning rate as 100 and 0.01. The results are summarized in Table 13.

From the experimental results, it can be found that $\tau$ has a large impact on the robustness of the detector. If we set lower $\tau$, the model focuses on the main task during the overall fine-tuning step, so the watermark is sacrificed to obtain better main task performance. However, if set higher $\tau$, the accuracy of the watermark is excessively considered, the model will continue to deepen the watermark. In addition to reducing the accuracy on the main task, the total computation time will become longer, and the robustness of the detector will also deteriorate. Because the detector will over-fit on the well-engraved watermark training data and has never seen detection training data with any augmentation. Thus, we can find that the watermarked models with high $\tau$ have relatively poor watermark accuracy after attacking.

Table 13: Re-embed Threshold $\tau$. To find the most suitable threshold, we vary the value of $\tau$ and evaluate the robustness of each setting.

| $\tau$   | 75.00 | 80.00 | 85.00 | 90.00 | 95.00 |
|---------|-------|-------|-------|-------|-------|
| main acc. (%) of Unwatermarked model | 95.30 |

Table 14: Fine-tuning attacks with different learning rate on CIFAR-10. We take the result with the highest main acc.

| lr = 0.001 | lr = 0.01 |
|------------|-----------|
| main acc. (%) | wm acc. (%) | main acc. (%) | wm acc. (%) |
| WNN (USENIX’18) | 90.72 | 100.00 | 92.43 | 52.31 |
| DeepIPR (NIPS’19) | 92.40 | 100.00 | 92.55 | 70.48 |
| PA (NIPS’20) | 94.07 | 100.00 | 92.26 | 70.73 |
| RIGA (WWW’21) | 94.43 | 100.00 | 93.34 | 99.24 |
| DAMN (MM’21) | 79.20 | 8.80 | 80.34 | 0.00 |
| CosWM (AAAI’22) | 94.95 | 88.35 | 95.00 | 82.97 |
| USP (Ours) | 93.38 | 98.60 | 93.84 | 86.28 |
| CSP (Ours) | 94.64 | 98.61 | 94.60 | 88.72 |

Table 15: Ablation Experiment of $L_{KLD}$ and Detector.

| $L_{KLD}$ | main acc. (%) | wm acc. (%) | $L_{KLD}$ |
|-----------|---------------|-------------|-----------|
| With $L_{KLD}$ and detector | 94.947 | 98.886 | 2.914 |
| Only with detector | 94.976 | 66.233 | - |
| Only with $L_{KLD}$ | 94.036 | 3.581 | - |
| Unwatermarked model $M_2$ | 93.989 | 5.105 | - |

E  ABLATION EXPERIMENT - KL DIVERGENCE LOSS AND DETECTOR

To know how the kl divergence loss ($L_{KLD}$) and the detector affect our methods, we conduct an ablation experiment on USP. Since there is a customized perturbation adding mechanism in CSP, it is not easy to see the direct impact of $L_{KLD}$ on the method. The results are showed in Table 15. First of all, if only the detector is used, the watermark accuracy becomes very low. We consider the reason is when the model updates its parameters without the objective of increasing $L_{KLD}$ makes the deviation in the output is not enough, then resulting in the poor effect of the detector. If only $L_{KLD}$ is used and no detector is used, there is no standard for judging whether the watermark exists. Here, we also train an unwatermarked model $M_2$ with a comparable main task accuracy. From Table 15, we can find the $L_{KLD}$ of $M_2$ is also large, so just using $L_{KLD}$ is also not enough.