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Extending Null Embedding for Deep Neural Network (DNN) Watermarking

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Abstract: The rise of Machine Learning (ML) has opened new business opportunities, particularly through Machine Learning as a Service (MLaaS), where costly models like Deep Neural Networks (DNNs) can be outsourced. However, this also raises concerns about model piracy. To protect against unauthorized use, watermarking techniques have been developed. One such method, null embedding by Li et al., disables the model if pirated but reduces classification accuracy. This paper proposes modifications to the null-embedding technique that reduce this impact and keep the classification accuracy close to that of a non-watermarked model.

1 INTRODUCTION

The growing popularity of Deep Neural Networks (DNN), along with the challenges of training and fine-tuning them, has led to the emergence of a new market: Machine Learning as a Service (MLaaS) (Ribeiro et al., 2016). Due to its economic growth and incentives, it has become crucial for ML developers to protect their models against piracy and infringement to protect their ownership rights. *Watermarking* is a well-known technique for protecting ownership upon copying and unauthorized distribution for various assets such as datasets (İşler et al., 2024), databases (Sion et al., 2004), and machine learning models (Adi et al., 2018). Watermarking consists of two algorithms: 1) *generation* (or embedding/insertion); and 2) *verification* (or extraction/detection). In the generation algorithm, a watermark is embedded to the original data by using a high entropy watermarking secret key. Later, an owner computes the verification algorithm on suspected data using its watermarking secret key to extract/detect the watermark which is used as a proof of ownership even if the data is modified (un)intentionally. Due to the imperceptibility property of watermarking schemes, watermarking does not affect the utility/functionality of the original data (e.g., a watermarked model having a very close accuracy compared to the original model).

Previous work on DNN watermarking relies on either *white-box* or *black-box* verification (Guo and Potkonjak, 2018). The white-box method requires access to the model's internal parameters, which is unrealistic when a model owner suspects piracy by a third party. In contrast, the black-box approach, where the owner verifies the watermark by querying the model, is more practical and secure. Most black-box methods use backdoors that trigger a specific output known only to the owner. However, these can be vulnerable if attackers discover the trigger behavior (Li et al., 2020). To address this, (Li et al., 2020) introduced *null embedding*, which ties the watermark to the model's accuracy—making piracy attempts break the model. While effective, this method can reduce accuracy by up to 1.5%, which may be unacceptable for performance-critical applications.

In this preliminary work, we propose a new DNN watermarking using the null embedding based on the work by (Li et al., 2020). Our modified approach improves the classification accuracy while maintaining the robust watermark against piracy attacks. We propose four new methods for the null embedding using four filters: 1) *random*; 2) *peripheral*; 3) *circular*; and 4) *triangular*. We later run extensive experiments to validate our claims on accuracy improvement using CIFAR-10 and MNIST datasets and compare our results with (Li et al., 2020). The results show that the

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non-watermarked model yields a validation set classification accuracy of $82.91 \pm 0.19\%$. The best of the proposed watermarking methods yields an accuracy of $82.79 \pm 0.17\%$, which is an improvement over $82.44 \pm 0.39\%$ from (Li et al., 2020).

2 RELATED WORK

(Uchida et al., 2017) proposes the first DNN watermarking, which is a white-box verifiable technique based on embedding a watermark in the parameters of the model. Their work is later used as the benchmark for requirement definitions such as fidelity and robustness in the DNN watermarking domain. (Zhang et al., 2018) proposed a black-box verifiable DNN watermarking method. Their technique used an idea from backdoor attacks on DNNs to embed the watermark. A train image is embedded with a pattern and this image has a label that it should not have (e.g., a watermarked car image results in the label 'plane').

Most black-box watermarking techniques are based on the backdoor approach introduced by (Zhang et al., 2018), where specific inputs trigger a known output for verification. (Guo and Potkonjak, 2018) investigated DNN watermarking in embedded systems and proposed using cryptographic techniques, such as embedding the owner's signature during training, to strengthen ownership verification.

All the aforementioned black-box watermarking techniques are insecure against piracy as shown by (Li et al., 2020). To mitigate piracy attacks, the same paper suggests null embedding, which is a technique that uses a bit sequence to build a strong dependency between the normal classification accuracy of the model and the watermark. This makes it impossible for attackers to remove the watermark or insert their own. This unique resistance against piracy is why we chose their technique to study further.

Algorithm 1: WMGenerate (sk, h, w, n).

Data: sk, h, w, n
Result: $\{bits, pos\}$
$\sigma \leftarrow \mathsf{Sign}(sk, v)$
$\{bits, pos\} \leftarrow \mathsf{Transform}\ (\sigma, h, w, n)$
return $\{bits, pos\}$

3 PRELIMINARIES

As in (Li et al., 2020), we utilize a collision-resistant hash function Hash (Katz and Lindell, 2014), a digital signature (Katz and Lindell, 2014) (Sign and SignVerify) where a private signing key and public verification key are denoted by *sk* and *vk*, respectively, and existing DNN training techniques.

3.1 Watermarking with Null Embedding

As mentioned, we base our watermarking on the null embedding of a watermark into the training dataset d of a DNN model $\mathcal{M}$ as proposed by (Li et al., 2020). The training set d consists of data points in a matrix format with dimensions of h (height) and w (width). Below, due to page limitations we briefly describe their watermark generation, embedding, and verification algorithms (see their paper for further details).

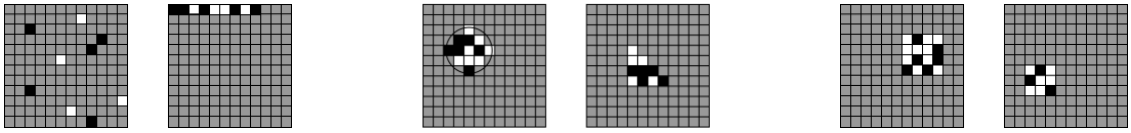
Generation. The watermark generation algorithm, see Algorithm 1, receives the following inputs: the owner's secret key *sk*, the height h and width w of the image to be watermarked, and the length of one side of the square filter n. First, a signature is generated using *sk* to sign v which is the concatenation of a verifier string and a timestamp, $v = str||time$. Afterwards, Transform is called. Transform uses hashes of σ and modulos to determine the tuple of the square's position, and the bit pattern embedded in it $\{bits, pos\}$, as shown in Algorithm 2.

Algorithm 2: Transform (σ, h, w, n).

Data: σ, h, w, n
Result: $\{bits, pos\}$
$bits \leftarrow \mathsf{Hash}(\sigma) \mod 2^{n^2}$;
$pos = (x, y) \leftarrow (\mathsf{Hash}(\sigma) \mod (h-n),$
$\mathsf{Hash}(\sigma) \mod (w-n))$;
return $\{bits, pos\}$

Embedding. Null embedding (Li et al., 2020) consists of applying a filter $filter$ to a matrix-like data format, which disguises part of the matrix as having extreme values outside the normal dataset range. This effectively reduces the learning space of the model. For example, a 32×32 image is null-embedded by a 6×6 square filter with pixel color values of either $\lambda = 2000$ or $-\lambda = -2000$, depending on the bit pattern. Because both values are far from the normal color range of $[0, 255]$, these pixels no longer serve a purpose in the image classification. $filter$ is essentially the watermark $\{bits, pos\}$ and the shape in which it will be applied. Figure 1c illustrates the *square* shape.

The embedding algorithm for a square $filter$ is shown by Algorithm 3 where the input variables include a (very) large number λ, and side length of the square filter n. The watermarked *subset* is then added back into the training set. If we chose 10% of images



(a) Random and Peripheral patterns (b) Circular and Triangular patterns (c) 4x4 and 3x3 Square patterns

Figure 1: Different embedding patterns on a 12x12 image. White squares are set to $\lambda = 2000$, black squares to $-\lambda$.

to watermark, the training set size increases by 10% (since each watermarked image in *subset* also has its unmarked counterpart). Finally, we train $\mathcal{M}$ on the augmented dataset.

Algorithm 3: EmbedSquare $(d, bits, pos, \lambda, n)$

Data: $\{d, bits, pos, \lambda, n\}$.
Result: Embedded Subset
(m = Most Significant Bit of $bits$)
$subset \leftarrow$ random sample from d
for $image \in subset$ **do**
  for $i \in [n]$ **do**
    for $j \in [n]$ **do**
      $image[i, j] \leftarrow m \cdot \lambda - (1 - m)\lambda$
      $bits << 1$
return *subset*

Algorithm 4: WMVerify $(d, vk, \sigma, h, w, n, T)$.

Data: $\{d, vk, \sigma, h, w, n, T\}$
Result: `Verified`/ `Rejected`
if SignVerify(vk, σ) **then**
  $(bits, pos) \leftarrow$Transform (σ, h, w, n);
  $d_{New} \leftarrow d +$ EmbedSquare $(d, bits, pos, \lambda, n)$;
  if $[Accuracy_{\mathcal{M}}(d_{New})] \geq T$ **then**
    return `Verified`;
  else
    return `Rejected`;

Verification. The verification algorithm, see Algorithm 7, receives the following inputs: the data d, the owner's public key vk and signature σ, the height h and width w of the input images, the length of one side of the square filter n, and a threshold T. Verification of the watermark is achieved by first checking if the owner's public key can verify the signature. Afterwards, a new set of watermarked data points are generated. This can be done by anyone who has access to Transform described in Algorithm 2. After generation, the trained model is asked to guess labels for the newly generated data points. The verification returns `Verified` if the model returns an accuracy higher than a certain pre-determined threshold T. Otherwise, verification fails and the algorithm returns `Rejected`.

4 MODIFICATIONS OF NULL EMBEDDING

The main idea behind our improved approach is to change the shape and position of the watermark so it doesn't interfere as much with normal model behavior, while still working effectively. The original method (Li et al., 2020) used a square patch placed randomly, which could block important parts of the image. Instead, we suggest using other shapes (i.e., random, peripheral, circular, or triangular patterns) that take up the same space but are arranged differently. These new patterns are less likely to cover key parts of the image, helping the model stay accurate while still including a clear watermark.

The original watermark method also introduced something called "true embedding," where the reverse of the watermark was used with wrong labels to test if a model was truly watermarked. While this adds an extra layer of proof, our results show it is not needed and just using the basic watermark is already very reliable, with almost no false positives. Adding true embedding makes things more complex and could hurt accuracy. With the simpler method and smarter watermark patterns, we keep strong protection while avoiding extra training or performance problems.

Algorithm 5: EmbedTriangular$(d, bits, pos, \lambda, n)$.

Data: $d, bits, pos, \lambda, n$
Result: Embedded Subset
(m = Most Significant Bit of $bits$)
$subset \leftarrow$ random sample from d
$k \leftarrow \frac{-1+\sqrt{1+8n^2}}{2}$
for $image \in subset$ **do**
  for $i \in [k]$ **do**
    for $j \in [i]$ **do**
      $image[i, j] \leftarrow m \cdot \lambda - (1 - m)\lambda$
      $bits << 1$
return *subset*

4.1 Types of Filters Considered

For our work, we use the following four filter patterns: *Random, Peripheral, Circular*, and *Triangular*. To keep the training domain at a similar size to images embedded with the original square pattern, all filters below were made to have the same pixel count as the original pattern (or close if not possible). For a different filter, we have to determine which pixels in the image belong to the watermark shape. For instance, for a square or rectangular patch, this is a contiguous block. For the peripheral filter, it could be the first few rows/columns (forming an L-shape) covering n pixels. For a circular filter, all pixels are within a radius r of the center point.

Random Filter. The random embedding pattern as illustrated in Figure 1a chooses the same number of pixels as the square filter (36 in our test) at random throughout the image. This has the effect of not blocking any significant features for the human eye, but is very similar to introducing noisy training samples into the training dataset. This can cause lower verifiability of the watermark as it is not perceivable, and potentially harm the classification accuracy.

Peripheral Filter. This filter as illustrated in Figure 1a is constructed by selecting the top-most and left-most pixels possible in the image for pattern embedding. This pattern was chosen as the extremes of a matrix-like data structure can be cropped without disturbing the coherency of the rest of the data. Especially in image datasets like the ones we used, the peripherals of the image tend to not have parts of the object being labeled from the image. This means that the classification accuracy is less affected than other methods of reducing the training domain.

Circular Filter. To embed this filter, a circle is chosen with a center pixel determined similarly to the filter position determination in Algorithm 2. Afterwards, the radius of a circle with equal surface area to the square is calculated, and pixels with centers within this circle are used to embed the bit pattern. This method was chosen as it will have the effect of minimizing the perimeter of the watermark shape. As DNNs use adjacent pixels to learn patterns, it improves to result in better classification accuracies in comparison to a square filter (see Figure 1b).

Triangular Filter. The triangular filter uses a triangle with an area less than or equal to that of the square to embed the bit pattern. Its reason for inclusion is to see if there are significant classification differences between using different regular polygon shapes for null embedding. Data in matrix form does not tend to have features that can be derived from a diagonal along the matrix. Therefore, we predict that it is less likely for a triangle to block a significant feature in comparison to a square. The number of rows in the triangular filter is determined as $k = \frac{-1+\sqrt{1+8x}}{2}$. The goal is to create the largest triangle where the i^{th} row has $\leq i$ elements, with the number of pixels not exceeding the number of pixels in the equivalent square filter. Given the number of pixels in the square filter as x, we want to find the largest integer k such that $\frac{k(k+1)}{2} \leq x$. Rearranging this inequality gives $k^2+k-2x=0$, and plugging $a=1$, $b=1$, $c=-2x$ into the quadratic formula yields $k = \frac{-1\pm\sqrt{1^2-4\cdot1\cdot(-2x)}}{2} = \frac{-1+\sqrt{1+8x}}{2}$. Algorithm 5 shows how this equation is used in the embedding.

5 EXPERIMENTAL SETUP AND ANALYSIS

5.1 Setup

All experiments were conducted on an HP ZBook Power G7 laptop with an NVIDIA Quadro T1000 GPU, using `Python`. We used SHA256 for hashing and RSA PKCS#1 v1.5 for digital signatures. The `CIFAR-10` (60K images) and `MNIST` (70K images) datasets, each with 10 class labels, were used for object and digit recognition, respectively. Models were built with TensorFlow 2.16 via the Keras API, running on Windows Subsystem for Linux (WSL2) to enable GPU support, as native Windows support was dropped after TensorFlow 2.10.

Data Split and DNN Structure. `CIFAR-10` was split to have 50K data points in the training set and 10K in the validation set. `MNIST` was split to have 60K data points in the training set and 10K in the validation set. 10% of the training dataset was selected randomly before each training to be embedded with the watermark. With the addition of the watermarked data, the total training set has a size of 55K for `CIFAR-10` and 66K for `MNIST`. To match the experimental setup from (Li et al., 2020), the DNN for training on `CIFAR-10` was constructed with 6 convolutional and 3 dense layers. The DNN for training on `MNIST` was constructed with 2 convolutional and 2 dense layers.

The model $\mathcal{M}_{\texttt{CIFAR-10}}$ on `CIFAR-10` was trained for 50 epochs in each round, while the `MNIST` DNN $\mathcal{M}_{\texttt{MNIST}}$ was trained for 20 epochs. This is because `MNIST` is a lot simpler, and thus the DNN achieves higher accuracy fast. For both datasets, the results obtained from 5 rounds of training were averaged out for each configuration presented in the following section.

Trials. Before experimenting with the aforementioned filter types in Section 4, the square filter used by (Li

Table 1: Performance Comparison of Watermarking Methods on CIFAR-10 and MNIST. Best accuracy values are bolded.

	Method	Training		Validation		Verification	
		Accuracy	Loss	Accuracy	Loss	Accuracy	Loss
CIFAR-10	**No Watermark**	98.56±0.12	0.04±0.00	82.91±0.19	0.85±0.01	12.14±1.26	73.61±27.75
	Square (Li et al.)	98.41±0.39	0.05±0.01	82.44±0.39	0.86±0.05	96.67±1.78	0.11±0.06
	Random	98.36±0.23	0.05±0.01	82.61±0.20	0.84±0.02	66.48±5.30	1.55±0.33
	Peripheral	98.74±0.15	0.04±0.00	82.60±0.30	0.88±0.02	**99.50±0.18**	0.02±0.01
	Circular	98.56±0.28	0.04±0.01	**83.01±0.27**	0.83±0.04	95.50±1.17	0.14±0.04
	Triangular	98.73±0.08	0.04±0.00	82.79±0.17	0.87±0.02	99.44±0.25	0.02±0.01
MNIST	**No Watermark**	99.86±0.03	0.00±0.00	99.42±0.03	0.02±0.00	95.15±4.37	0.17±0.17
	Square (Li et al.)	99.83±0.07	0.01±0.00	99.43±0.03	0.02±0.00	99.60±0.52	0.01±0.01
	Random	99.85±0.03	0.01±0.00	**99.44±0.03**	0.02±0.00	99.17±0.67	0.03±0.02
	Peripheral	99.87±0.01	0.00±0.00	99.41±0.04	0.02±0.00	99.98±0.02	0.00±0.00
	Circular	99.83±0.06	0.01±0.00	99.38±0.03	0.02±0.00	99.62±0.32	0.01±0.01
	Triangular	99.88±0.02	0.00±0.00	99.43±0.03	0.02±0.00	**99.99±0.01**	0.00±0.00

et al., 2020) was implemented following the pseudocode procedure in their paper. The results obtained from the DNN watermarked with the square pattern were then used as the benchmark to compare the performance of our proposed pattern varieties. Additionally, the model was trained with the same parameters but without a watermark to be able to compare the loss of accuracy on the validation set.

5.2 Evaluation Metrics

For our experiments, we evaluate our approach on each aforementioned datasets using two metrics for each *training*, *validation*, and watermark *verification*: 1) *Accuracy*; and 2) *Loss*. Sparse Categorical Cross-Entropy is used as the loss function. This loss function was chosen to keep the results comparable with the experimentation performed in (Li et al., 2020). After each training round, the epoch after which $\mathcal{M}$ yielded the highest accuracy for the validation set was used as the representative data for that round. This epoch was usually between the 40th-50th for $\mathcal{M}_{\texttt{CIFAR-10}}$ and the 15th-20th for $\mathcal{M}_{\texttt{MNIST}}$. The reason of later epochs sometimes performing worse is that the model starts overfitting to the training set after a certain number of epochs.

Table 1 shows the average values from 5 trials for each watermarking method. The results from the models on the training data, validation data, and watermark verifiability are explained below.

Training Data. The accuracy and loss of each embedding method on the training data are shown in Table 1 under **Training**. For models trained for the same number of epochs on the same size dataset, these values are expected to be similar regardless of the embedding method.

Validation Data. Validation results are key for comparing the impact of different watermarking methods on model accuracy. As shown in Table 1 (**Validation**), our proposed patterns reduce accuracy loss compared to the original square filter; hence confirming the effectiveness of our modifications.

Watermark Verifiability. This metric is important as it is a hard requirement for any watermarking method to be verifiable in the models they are embedded in. If a watermarking method yields high accuracy in the original classification task but is not verifiable, then it is not a functioning watermark. The accuracy and loss of each embedding method in detecting the watermark are shown in Table 1 under **Verification**.

5.3 Analysis

Before discussing the results as presented in Table 1, it is worth to note that some watermarked models have a higher accuracy than the non-watermarked (non-WM) model on the training set. This indicates that the high number of epochs used for training made the accuracies of watermarked and non-WM models indistinguishable. Thus, the training accuracy has essentially saturated, and further training is unlikely to yield any significant improvement.

The model embedded with a random pattern performed significantly worse than the other watermarked models in terms of watermark verification. Therefore, we excluded this randomly watermarked model when determining the verifiability threshold for either dataset since it would skew the threshold due to its poor verification performance.

CIFAR-10 Dataset. Among the models trained on CIFAR-10, the circular pattern watermark achieved the highest average validation accuracy, slightly outperforming the non-watermarked model, though still within one standard deviation (SD). The triangular pattern also fell within one SD but showed lower variability than the circular one, suggesting more consis-

tent performance. Both circular and triangular patterns had lower SDs than the square pattern, which also converged more slowly to a validation accuracy of around 82%. For watermark verification, a threshold of $T = 90\%$ proved effective. The peripheral pattern showed the best verification results, closely followed by the triangular pattern, making the triangular pattern the most balanced choice overall.

`MNIST` Dataset. On `MNIST`, the classification task was significantly easier for the trained DNNs (baseline $\sim 99.4\%$ accuracy). Therefore, the training set classification accuracy quickly converges to values higher than 99%. Similarly in the validation set accuracy, all watermarking methods have yielded an accuracy of around 99.4%. The fact that almost all of the validation accuracies lie within an SD of each other means that it is difficult to infer much from these values. Our results show that the Square and Random watermarked models have performed closest to the non-WM model. Even though the Random watermarked model appears to have the most accurate and reliable validation set, its performance in verifiability is significantly lower than the other watermarked models. The Triangular watermarked model offers the best watermark verifiability among all methods tested. Combined with its validation accuracy, which closely matches the non-watermarked model, it proves to be the most effective option. Our results suggest that a verification threshold of $T = 99\%$ is suitable.

Comparison with Li et al. Compared to the results in (Li et al., 2020), our findings show some notable differences. First, our `CIFAR-10` models did not reach the reported 88% normal classification (NC) accuracy, despite closely following the original procedure. Even with 100 training epochs, accuracy stayed around 84%, likely due to hardware limitations. In contrast, our `MNIST` models achieved over 99% NC accuracy, exceeding the 98.7% reported by (Li et al., 2020). While they used a 50% embedding rate for `MNIST`, we found no benefit in doing so and used a consistent 10% rate for both datasets. On `CIFAR-10`, models using circular or triangular watermark patterns performed about 0.5% better in NC accuracy than those using the square pattern. This suggests that non-square shapes are more effective for preserving model accuracy when using null embedding.

6 FUTURE WORK AND CONCLUSION

We proposed four new ways to embed a watermark into a DNN with the null embedding method from (Li et al., 2020). Experiments on `CIFAR-10` showed that the circular pattern preserves model accuracy best, improving performance by about 0.5% compared to the square pattern and matching the accuracy of a non-watermarked model. Future work includes testing the impact of transfer learning and fine-tuning.

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