Access Control with Encrypted Feature Maps for Object Detection Models

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SUMMARY In this paper, we propose an access control method with a secret key for object detection models for the first time so that unauthorized users without a secret key cannot benefit from the performance of trained models. The method enables us not only to provide a high detection performance to authorized users but to also degrade the performance for unauthorized users. The use of transformed images was proposed for the access control of image classification models, but these images cannot be used for object detection models due to performance degradation. Accordingly, in this paper, selected feature maps are encrypted with a secret key for training and testing models, instead of input images. In an experiment, the protected models allowed authorized users to obtain almost the same performance as that of non-protected models but also with robustness against unauthorized access without a key.

1. Introduction

Deep neural networks (DNNs) and convolutional neural networks (CNNs) have been deployed in many applications such as biometric authentication, automated deriving, and medical image analysis [1]. However, training successful DNNs and CNNs requires three ingredients: a huge amount of data, GPU accelerated computing resources, and efficient algorithms, and it is not a trivial task. In fact, collecting images and labeling them is also costly and will also consume a massive amount of resources. Moreover, algorithms used in training a model may be patented or have restricted licenses. Therefore, trained DNNs and CNNs have great business value. Considering the expenses necessary for the expertise, money, and time taken to train a model, a model should be regarded as a kind of intellectual property (IP).

There are two aspects of IP protection for DNN models: ownership verification and access control [2]. The former focuses on identifying the ownership of the models, and the latter addresses protecting the functionality of the models from unauthorized access. Ownership verification methods were inspired by digital watermarking [3] and embed watermarks into models so that the embedded watermarks can be used to verify the ownership of the models in question [4][13].

Although the above watermarking methods can facilitate in identifying the ownership of models, in reality, a stolen model can be exploited in many different ways. For example, an attacker can use a model for their own benefit without arousing suspicion, or a stolen model can be used for model inversion attacks [14] and adversarial attacks [15][17]. Therefore, it is crucial to investigate mechanisms to protect models from authorized access and misuse. In this paper, we focus on protecting a model from misuse when it has been stolen (i.e., access control).

A method for protecting models against unauthorized access was inspired by adversarial examples and proposed to utilize secret perturbation to control the access of models [18]. In addition, another study introduced a secret key to protect models [19][20], and it was shown to outperform the other methods. The secret key-based protection method uses a key-based transformation that was originally used by an adversarial defense in [21], which was in turn inspired by perceptual image encryption methods [22][23]. This block-wise model protection method utilizes a secret key in such a way that a stolen model cannot be used to its full capacity without a correct secret key. The robustness of these methods to attacks done to exploit protected models has already been verified, but all previous model-protection methods focus on the access control of image classification models.

Therefore, for the first time, in this paper, we propose a model protection method for object detection models by applying a key-based transformation to feature maps. The method not only achieves a high accuracy (i.e., almost the same accuracy as in the non-protected case), but also increases the key space substantially. We make the following contributions in this paper.

- We point out that the block-wise image encryption that is used for access control of image classification models is not useful for that of object detection models.
- We propose an access control method with a secret key for object detection models for the first time, which enables us not only to maintain a high accuracy but also to increase the key space.

In an experiment, the proposed model-protection method is confirmed to outperform conventional methods with encrypted images.

2. Related Work

There are two approaches to protecting trained models: ownership verification and access control. These approaches are reviewed to clarify problems with existing methods.

2.1 Ownership Verification

Ownership verification focuses on identifying the ownership
of trained models. Researchers have developed model watermarking methods inspired by digital watermarking. In these methods, a watermark is embedded into a DNN model during the training phase, and the embedded watermark is used to claim ownership when the model is used without authorization.

There are two scenarios for the model watermarking methods: the whitebox scenario and the blackbox scenario. The first model watermarking method was proposed in [5], in which a watermark is embedded into one or more convolution layers of a model by using an embedding loss function. Similar methods were presented in [6]-[8]. When extracting a watermark, these methods need access to model weights, so a whitebox scenario is assumed. However, trained models, including pirated ones, are often provided as an online service. In such a situation, an inspector needs an ownership verification method that uses only inputs and predictions, so a blackbox scenario has to be considered. Several watermarking methods have been investigated to consider the black-box scenario such as in [8]-[13]. In [12]-[13], a model owner installs a backdoor to output a predefined label for a particular input, like a kind of adversarial example. Other methods extract a watermark pattern from the predictions of a protected model by using specific training samples [8], [11].

However, model watermarking methods aim for only ownership verification. Therefore, stolen models can be directly used by unauthorized users, so we focus on access control to protect trained models from unauthorized access even if the models are stolen.

2.2 Access Control

Another approach to protecting trained models is access control that aims to protect the functionality of DNN models from unauthorized access. Therefore, protected models are required not only to provide a high accuracy to authorized users but also low performance to unauthorized users. In addition, since an unauthorized user may steal trained models to illegally use them, protected models have to be robust against various attacks.

The first access control method, which was inspired by adversarial examples [15]-[17], was proposed for image classification models in [18]. In this method, authorized users add a secret perturbation generated by an anti-piracy transform module to input images, and the processed input images are fed to a protected model. Therefore, this method needs additional resources to train the module. In addition, the method focuses on protecting image classification models.

The second method is to extend the passport-based ownership verification method [8] as an access control method. However, the passport in [8] is a set of extracted features of a secret image/images or equivalent random patterns from a pretrained model. In addition, a network has to be modified with additional passport layers to use passports. Therefore, there are significant overhead costs in both the training and inference phases. Moreover, the effectiveness of the passport-based method has never been confirmed under the use of object detection models.

The third is a block-wise image transformation method with a secret key [19]-[20], which is inspired by learnable image encryption [21]-[26]. In this method, input images are encrypted with a key, for which three types of encryption methods: negative/positive transformation (NP), pixel shuffling (SHF), and format-preserving Feistel-based encryption (FFX), were proposed. Fig. 1 shows the framework of the block-wise method. In the framework, an owner transforms all training images with secret key $K$, and a model is trained to protect the model by using the transformed images and
corresponding ground truths. An authorized user with key $K$ transforms a test image with K and feeds it to the protected model to get a prediction result with high accuracy. In contrast, an unauthorized user without key $K$ cannot obtain a prediction result with high accuracy, even if the unauthorized user knows the framework and the encryption algorithm. In addition, the method with key $K$ does not need any network modification or incur significant overhead costs. However, the use of the block-wise transformation is limited to image classification tasks, because the block-wise transformation cannot provide a pixel-level resolution that is required to protect object detection models.

Accordingly, in this paper, we propose a novel access control method for object detection tasks for the first time. The proposed method does not need any network modification or incur significant overhead costs as well.

3. Proposed Access Control with Encrypted Feature Maps

Access control of object detection models with encrypted feature maps is proposed here.

3.1 Overview

Protected models for access control should satisfy the following requirements. The protected models should provide prediction results with a high accuracy to authorized users but not provide such high-accuracy results to unauthorized users. To satisfy these requirements, encrypted feature maps are used as shown in Fig. 3. In the framework with encrypted feature maps, an image owner trains a model by using plain training images and corresponding ground truths, where selected feature maps in the network are encrypted by using a secret key $K$ at each training iteration in accordance with the proposed method. For testing, an authorized user with key $K$ feeds a test image to the trained model to obtain a prediction result with high accuracy. In contrast, when an unauthorized user without key $K$ inputs a test image to the trained model without any key or with an estimated key $K'$, the unauthorized user cannot benefit from the performance of the trained model. The goal of object detection is to understand the regions and classes of objects present in an image. Fig. 3 shows an example of object detection. Object detection detects the location of objects in the input image as rectangles, and classifies the class of each object.

3.2 Feature Map

In the proposed method, a feature map in a network is selected, and the selected feature map is encrypted with a secret key. In this paper, SSD300 [30] based on VGG-16 [31] is used as an object detection model, where SSD300 has 11 feature maps as illustrated in Fig. 3. In the proposed method, one feature map is selected from the feature maps, and it is encrypted with a key.

As shown in Fig. 3, a feature map has a shape of $(c, h, w)$, where $c$, $h$, and $w$ are the channel, height, and width of the feature map, respectively. A color input image has $c = 3$, but $c$ of a feature map is much larger in general. That is why we use a feature map.

3.3 Feature Map Encryption

In the conventional methods for image classification tasks, input images are encrypted with a key in accordance with a block-wise encryption method [19]. In contrast, in the proposed method, a feature map is encrypted in accordance with a pixel-wise encryption method so that results with a pixel-level resolution are obtained, because block-wise encryption cannot obtain such a resolution that is required to protect object detection models.

A selected feature map $x$ is transformed with a key $K$ at each iteration for training a model. To transform a feature map, pixel shuffling (SHF) used in image classification tasks is extended to be applied to object detection models in terms of two points: the use of feature maps and a block size of $M = 1$. The extended encryption is called channel permutation (CP). Accordingly, CP is a pixel-wise transformation, where a feature map is permuted only along the channel dimension (see Fig. 3). The following is the procedure of CP.

1) Select a feature map $x$ to be encrypted.
2) Split $x$ into blocks with a size of $M$ as

$$B = \{ B_{(1,1)}, \ldots, B_{(i,j)}, \ldots, B_{(h/M,w/M)} \}, \quad (1)$$

where $h$ and $w$ are assumed to be dividable by $M$ for the sake of simplicity, and $M = 1$ is chosen for CP.
3) Flatten each block $B_{(i,j)}$ into a vector as

$$b_{(i,j)} = [b_{(i,j)}(1), \ldots, b_{(i,j)}(L)], \quad (2)$$

where $L$ is $c \times M \times M$.
4) Generate a secret key as

$$\alpha = [\alpha_{1}, \ldots, \alpha_{i}, \ldots, \alpha_{i'}, \ldots, \alpha_{L}], \quad (3)$$

where $\alpha_{i} \in \{1, \ldots, L\}$ and $\alpha_{i} \neq \alpha_{i'}$ if $i \neq i'$.
5) Permute each vector $b_{(i,j)}$ with $\alpha$ as

$$b'_{(i,j)}(i) = b_{(i,j)}(\alpha_{i}), \quad (4)$$

and get a permuted vector such as

$$b'_{(i,j)} = [b'_{(i,j)}(1), \ldots, b'_{(i,j)}(L)]. \quad (5)$$
Table 1: Key space of encryption methods

| Encryption Method | Key space | Remark |
|-------------------|-----------|--------|
| SHF [19]          | \((c \times M \times M)!\) | \(c = 3\) |
| CP                | \(c!\)    | \(c > 3\) |

6) Concatenate the permutated vectors to form an encrypted feature map \(x'\) with a dimension of \((c, h, w)\).

The above procedure corresponds to that of a block-wise image encryption used in image classification tasks [19]. If \(x\) is an input image, and \(M\) is larger than \(M = 1\), as illustrated in Fig. 4, Fig. 5 also shows an example of images transformed by using the block-wise encryption.

3.4 Difference between SHF and CP

The differences between SHF for image classification models and CP for object detection ones are summarized as below.

(a) CP is a pixel-wise transformation.
(b) CP is applied to a feature map.
(c) The number of feature map channels is larger than that of input image channels.

Difference (a) allows us to obtain results with a pixel-level resolution, but pixel-wise transformations are not robust against various attacks if the transformation is applied to input images as discussed in [19] because the number of input image channels \(c\) is small (i.e., RGB images have \(c = 3\)).

In Table 1, the key space of SHF is compared with that of CP. For SHF, the key is decreased if a small block size is chosen. For example, if SHF with \(M = 1\) is applied to an input image, the key space is \(3! = 6\). In contrast, when a feature map with \(c = 256\) is encrypted by using CP, the key space is \(256! \approx 2^{1684}\). In general, the channel number of feature maps is much larger than that of input images, so CP has a large key space even when \(M = 1\) is selected, compared with SHF. In addition, when using CP, the attacker has to know or estimate the location of the transformed feature map, which cannot be known from the model itself. In our scenario, the model owner is assumed to securely manages both the location of transformed feature maps and the key. Accordingly, the attacker cannot know the location of the transformed feature map from the network.

3.5 Threat model

A threat model includes a set of assumptions such as an attacker’s goals, knowledge, and capabilities. Users without secret key \(K\) are assumed to be the adversary. Attackers may steal a model to achieve different goals for profit. In this paper, we consider the attacker’s goal is to be able to make use of a stolen model. We assume that authorized users know key \(K\), and the model owner securely manages both the location of transformed feature maps and key \(K\). In addition, the model protection method is also assumed to be disclosed except for key \(K\) and the location of transformed feature maps. To use
4. Experimental Results

To confirm the effectiveness of the proposed method, we evaluated it in terms of access control and robustness against unauthorized access. All the experiments were conducted using the PyTorch library in Python.

4.1 Setup

As an object detection model, we used the SSD300 pre-trained by using the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) CLS-LOC dataset. To apply the model to an object detection task, the pre-trained model was then fine-tuned by using two datasets.

4.1.1 PASCAL VOC

The PASCAL visual object classes (VOC) challenge 2007 and 2012 trainval datasets were used to fine-tune the pre-trained model. The PASCAL VOC 2007 was also used for testing. These datasets have 20 categories, including people, dogs, and so on. For data augmentation, the random sample crop, horizontal flip, and some photometric distortions described in were used for training models. In addition, due to the restrictions of SSD300 shown in Fig.

stolen models, the adversary has to get all of the location of transformed feature maps, key $K$ and the algorithm with $K$ for testing a query image. Accordingly, if the adversary can get these three items, it is possible to use the models, but the adversary does not know the location of transformed feature maps and the algorithm for testing a query image in general even in the case of a malicious legitimate user or collusion attacks. However, the adversary can be a spoofed-authorized user if he/she gets key $K$ from a malicious legitimate user or in some way. As a result, in that case, the adversary can illegally use the protected model.

Fig. 6: Input image encryption [19]

Fig. 7: Examples of encrypted image with pixel shuffling ($M = \text{block size}$)
input images were resized to $300 \times 300$ pixels. Models were trained by using a stochastic gradient descent (SGD) optimizer with an initial learning rate of $10^{-3}$, a momentum value of 0.9, a weight decay value of 0.0005, and a batch size of 32. Models were trained for 60k iterations with a learning rate of $10^{-3}$. The models were then trained for 20k iterations with a learning rate of $10^{-4}$ and 40k iterations with a learning rate of $10^{-5}$. The overall objective loss function was a weighted sum of the localization loss and the confidence loss. In this paper, the confidence loss was the cross-entropy loss over multiple classes, and the localization loss was the Smooth L1 loss between the predicted position and the ground truth position.

4.1.2 MS COCO

Another dataset called MS COCO was also used to fine-tune the pre-trained model. The pre-trained model was fine-tuned by using the COCO2014 train dataset [56], 10,000 images, which were randomly selected from the COCO2014 validation dataset [56], were used as test images. In object detection tasks, the datasets have 80 categories, so they are more difficult than the PASCAL VOC dataset.

In the experiment, we used the same data augmentation, model structure, and losses as the PASCAL VOC dataset except for the number of model iterations. Models were trained for 160k iterations at a learning rate of $10^{-3}$. The models were then trained 40k iterations at a learning rate of $10^{-4}$ and 40k iterations at a learning rate of $10^{-5}$.

4.2 Metric for Evaluating Detection Performance

Mean average precision (mAP) [30] was used as a metric for evaluating detection performance, which is a common evaluation metric for object detection. In this paper, the mAP of the PASCAL VOC dataset was calculated in accordance with the calculation method used in the PASCAL VOC 2007 [44] as follows.

First, intersection over union (IoU) [37] for each object is calculated by

$$IoU = \frac{A_{truth} \cap A_{pred}}{A_{truth} \cup A_{pred}},$$

where $A_{truth}$ represents the rectangular area of a ground truth, and $A_{pred}$ is a predicted rectangular area. Precision and recall are then defined for each class label as

$$Precision = \frac{TP}{TP + FP},$$

$$Recall = \frac{TP}{TP + FN},$$

where $TP$ (true positive) is the number of predicted objects for which there exists a ground truth object that satisfy two conditions: the same class label as that of the ground truth object, and $IoU \geq 0.5$. $FP$ (false positive) is the number of predicted objects that do not satisfy the conditions, and $FN$ (false negative) is the number of ground truths that are not detected.

Then, average precision (AP) for each class is calculated by using precision and recall in Eqs. (7) and (8). Finally, a mean average precision (mAP) value is calculated as

$$mAP = \frac{1}{N} \sum_{class=1}^{N} AP_{class},$$

where $N$ is the number of classes and $AP_{class}$ is the AP value of each class. The mAP ranges from 0 to 1, where when a mAP value is closer to 1, it indicates a higher accuracy.

In addition, we used the Python version of COCO API published by MS COCO to evaluate the MS COCO dataset. Among the results obtained from COCO API, mean average precision (mAP) under three different values of IoU (0.5, 0.75, 0.5:0.95) was used in the experiment, where 0.5:0.95 represents taking the average of the AP values when a value of IoU is changed from 0.5 to 0.95 in 0.05 increments.

4.3 Detection Result under Encrypted Input Images

First, input images were encrypted in accordance with SHF under various block sizes (i.e., $M \in \{1, 4, 12, 20, 60\}$) for comparison with the proposed method (CP) on the PASCAL VOC dataset. SHF was already demonstrated to achieve a high access control performance in image classification tasks in [19], but it has never been applied to object detection ones.

Table 2 shows experiment results, where “Correct ($K$)” means the use of test images encrypted with correct key $K$, and “No-enc” indicates the use of plain test images. “Baseline” also indicates the use of plain test images and models trained with plain images. “Incorrect ($K'$)” means the use of randomly generated key $K'$, where each value of Incorrect ($K'$) was calculated by averaging the values of 100 tests. From the results, even when correct key $K$ was used, the accuracy decreased significantly as block size $M$ increased. In contrast, when the block size was small, the protected model achieved a high accuracy close to the baseline. However, the accuracy without the encryption (i.e., No-enc) or with “Incorrect” was almost the same as that of “Correct,” so the access control was weak under the use of a small block size due to a small key space.

4.4 Detection Result under Encrypted Feature Maps

A selected feature map was transformed with key $K$ in accordance with the procedure in sec. 3.3. Table 3 shows

| method | block size | Correct ($K$) | No-enc | Incorrect ($K'$) |
|--------|------------|--------------|--------|------------------|
| pixel shuffling (SHF) | 1 | 0.7110 | 0.3958 | 0.7603 |
| | 4 | 0.7154 | 0.5745 | 0.3883 |
| | 12 | 0.4891 | 0.1976 | 0.0910 |
| | 20 | 0.0083 | 0.0086 | 0.0085 |
| | 60 | 0.1284 | 0.0480 | 0.0416 |

Table 2: Detection accuracy (mAP) of models with encrypted input images (PASCAL VOC dataset)
experimental results on the PASCAL VOC dataset, where Model-1 means that feature map 1 was selected for encryption. Figure 8 also shows an example of detected objects, in which feature map 4 was encrypted. From Table 3 and Fig. 8, the proposed method (CP) was confirmed to achieve almost the same accuracy as that of the baseline under the use of the correct key when feature map 2, 4, 5, 6, or 7 was selected. In contrast, CP provided a low accuracy to unauthorized users both without the key (No-enc) and with an incorrect key.

Table 3 also shows experimental results of using the proposed method on the MS COCO dataset where we focused on six models from Model-1 to Model-6, which achieved a high performance on the PASCAL VOC dataset. From the table, the proposed method was confirmed to be able to have almost same performance as that of Baseline as well as the use of the PASCAL VOC dataset, when correct key \( K \) was used. In contrast, when without correct key \( K \), the accuracy was heavily degraded as well.

Accordingly, CP with an encrypted feature map was effective in the access control of object detection models.

4.5 Robustness against Random Key Attack

CP was evaluated in terms of robustness against the random key attack that is to use test images encrypted with a randomly generated key. An evaluation was carried out on robustness with 100 incorrect keys. Fig. 8 shows the detection performance of the protected models under the use of the incorrect keys on the PASCAL VOC dataset. From the results of using CP, the mAP values were significantly low for all selected feature maps: Model-4, Model-5 and Model-6, so the models were robust enough against this attack. Also, the mAP values of using SHF were high. Therefore, the proposed method (CP) outperformed the conventional method (SHF) in terms of robustness against the random key attack.

From Table 3, the performance of models trained with an encrypted feature map depended on the selection of feature maps. We think that the difference in accuracy among the selected feature maps was caused by the architecture of the SSD300. From Fig. 8, the SSD uses multiple layers for feature learning. Therefore, for Model-10, only layer 11 is affected by encryption, so layers 4, 7, 8, and 9 can use almost the same features as the baseline model. In other words, the use of a deeper feature map makes the influence of CP weaker.

4.6 Impact of CP on training

Model-5 with CP was compared with Baseline in terms of the time required for each iteration and the speed of learning convergence. The average time of Baseline was 0.1670 sec and that of Model-5 was 0.2169 sec for each iteration where the machine specs used for evaluating the execution time were listed in Table 4. The use of CP was confirmed to slightly increase the time required for each iteration.

In Table 6, the speed of learning convergence with CP was compared with that without CP (Baseline). From the table, the learning convergence of the method with CP was
Table 4: Detection accuracy (mAP) of proposed models (COCO dataset)

| Selected feature map | 0.5 | 0.75 | 0.95 |
|----------------------|-----|------|------|
|                      | Correct (%) | No-corr | Incorrect (%) | Correct (%) | No-corr | Incorrect (%) | Correct (%) | No-corr | Incorrect (%) |
| Model-1              | 0.149 | 0.020 | 0.002 | 0.272 | 0.041 | 0.004 | 0.149 | 0.018 | 0.001 |
| Model-2              | 0.139 | 0.004 | 0.000 | 0.253 | 0.009 | 0.001 | 0.138 | 0.003 | 0.000 |
| Model-3              | 0.135 | 0.000 | 0.000 | 0.249 | 0.001 | 0.000 | 0.135 | 0.000 | 0.000 |
| Model-4              | 0.149 | 0.045 | 0.045 | 0.271 | 0.102 | 0.101 | 0.148 | 0.036 | 0.036 |
| Model-5              | 0.152 | 0.046 | 0.046 | 0.277 | 0.105 | 0.105 | 0.152 | 0.036 | 0.036 |
| Model-6              | 0.152 | 0.047 | 0.047 | 0.276 | 0.107 | 0.107 | 0.152 | 0.038 | 0.038 |
| Baseline             | 0.150 |       |       | 0.275 |       |       | 0.151 |       |       |

Fig. 9: mAP values of protected models with 100 incorrect keys (PASCAL VOC dataset). Boxes span from first to third quartile, referred to as $Q_1$ and $Q_3$, and whiskers show maximum and minimum values in range of $[Q_1 - 1.5(Q_3 - Q_1), Q_3 + 1.5(Q_3 - Q_1)]$. Band inside box indicates median. Outliers are indicated as dots.

Table 5: Machine spec used for evaluating executing time

| Processor | OS | Memory (CPU) | Memory (GPU) |
|-----------|----|--------------|--------------|
| Intel(R) Core(TM) i7-4790K CPU @ 4.00GHz | Ubuntu 18.04.6 LTS | Quadro RTX 6000 | 32GB | 24GB |

Table 6: Learning convergence speed with and without CP (PASCAL VOC dataset)

| No. of iterations | Loss value | Model-5 |
|-------------------|------------|---------|
|                   | Baseline   |         |
| 20000             | 3.5232     | 3.2191  |
| 40000             | 2.9450     | 3.1328  |
| 80000             | 2.3215     | 2.2475  |
| 120000            | 1.8859     | 2.0459  |

almost the same as that without CP.

5. Conclusion

In this paper, we proposed an access control method for object detection models for the first time. The method is carried out by encrypting a selected feature map with a secret key called channel permutation (CP), while input images are encrypted by using a block-wise encryption method in conventional methods. The use of CP allows us not only to obtain a pixel-level accuracy that is required for object detection but also to maintain a large key space even when a pixel-wise permutation is used. As a result, the proposed method can maintain both a high accuracy and robustness against attacks. In experiments, the conventional method with encrypted input images was not effective in the access control of object detection models, and the effectiveness of the proposed method was demonstrated in terms of detection accuracy. As future work, the proposed method with a encrypted feature map will be applied to other models to verify the effectiveness and limitations of CP.

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References

[1] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” nature, vol.521, no.7553, pp.436–444, 2015.
[2] H. Kiya, M. AprilPyone, Y. Kinoshita, S. Imaizumi, and S. Shiota, “An overview of compressible and learnable image transformation with secret key and its applications,” APSIPA Transactions on Signal and Information Processing, vol.11, 1, e11, 2022.
[3] M. Swanson, M. Kobayashi, and A. Tewﬁk, “Multimedia data-embedding and watermarking technologies,” Proceedings of the IEEE, vol.86, no.6, pp.1064–1087, 1998.
[4] M. Xue, J. Wang, and W. Liu, “Digital intellectual property protection: Taxonomy, attacks and evaluations,” Proceedings of the 2021 on Great Lakes Symposium on VLSI, pp.455–460, 2021.
[5] Y. Uchida, Y. Nagai, S. Sakazawa, and S. Sato, “Embedding watermarks into deep neural networks,” Proceedings of the 2017 ACM on International Conference on Multimedia Retrieval, pp.269–277, 2017.
[6] B. Darvish Rouhani, H. Chen, and F. Koushanfar, “Deepsigns: An end-to-end watermarking framework for ownership protection of deep neural networks,” Proceedings of the Twenty-Fourth International Conference on Architectural Support for Programming Languages and Operating Systems, pp.485–497, 2019.
[7] H. Chen, B.D. Rouhani, C. Fu, J. Zhao, and F. Koushanfar, “Deepmarks: A secure fingerprinting framework for digital rights management of deep learning models,” Proceedings of the 2019 on International Conference on Multimedia Retrieval, ICMR ’19, New York, NY, USA, p.105–113, Association for Computing Machinery, 2019.
[8] L. Fan, K.W. Ng, and C.S. Chan, “Rethinking deep neural network ownership verification: Embedding passports to defeat ambiguity attacks,” Advances in Neural Information Processing Systems, vol.32, pp.4716–4725, 2019.
[9] E. Le Merrer, P. Pérez, and G. Trédan, “Adversarial frontier stitching for remote neural network watermarking,” Neural Computing and Applications, vol.32, no.13, pp.9233–9244, July 2019.
[10] S. Sakazawa, E. Myodo, K. Tsaka, and H. Yanagihara, “Visual decoding of hidden watermark in trained deep neural network,” 2019.
IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), pp.371–374, 2019.

[11] M. Aprigliano and H. Kiya, “Privacy-resistant dnn watermarking by block-wise image transformation with secret key,” Proceedings of the 2021 ACM Workshop on Information Hiding and Multimedia Security, pp.159–164, 2021.

[12] J. Zhang, Z. Gu, J. Jang, H. Wu, M.P. Stoecklin, H. Huang, and I. Molloy, “Protecting intellectual property of deep neural networks with watermarking,” Proceedings of the 2018 on Asia Conference on Computer and Communications Security, pp.159–172, 2018.

[13] Y. Adi, C. Baum, M. Cisse, B. Pinkas, and J. Keshet, “Turning your weakness into a strength: Watermarking deep neural networks by backdooring,” 27th USENIX Security Symposium (USENIX Security 18), Baltimore, MD, pp.1615–1631, USENIX Association, Aug. 2018.

[14] M. Fredriksson, S. Jha, and T. Ristenpart, “Model inversion attacks that exploit confidence information and basic countermeasures,” Proceedings of the 22nd ACM SIGSAC Conference on Computer and Communications Security, CCS ’15, New York, NY, USA, p.1322–1333, Association for Computing Machinery, 2015.

[15] C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, and R. Fergus, “Intriguing properties of neural networks,” International Conference on Learning Representations, 2014.

[16] I. Goodfellow, J. Shlens, and C. Szegedy, “Explainable and harnessing adversarial examples,” International Conference on Learning Representations, 2015.

[17] N. Papernot, P. McDaniel, I. Goodfellow, S. Jha, Z.B. Celik, and A. Swami, “Practical black-box attacks against machine learning,” Proceedings of the 2017 ACM on Asia Conference on Computer and Communications Security, ASIA CCS ’17, New York, NY, USA, p.506–519, Association for Computing Machinery, 2017.

[18] M. Chen and M. Wu, “Protect your deep neural networks from piracy,” 2018 IEEE International Workshop on Information Forensics and Security (WIFS), pp.1–7, IEEE, 2018.

[19] M. Aprigliano and H. Kiya, “A protection method of trained cnn model with a secret key from unauthorized access,” APSIPA Transactions on Signal and Information Processing, vol.10, p.e10, 2021.

[20] M. Aprigliano and H. Kiya, “Training dnn model with secret key for model protection,” 2020 IEEE 9th Global Conference on Consumer Electronics (GCCE), pp.818–821, 2020.

[21] M. Aprigliano and H. Kiya, “Block-wise image transformation with secret key for adversarially robust defense,” IEEE Transactions on Information Forensics and Security, vol.16, pp.2709–2723, 2021.

[22] M. Tanaka, “Learnable image encryption,” 2018 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW), pp.1–2, 2018.

[23] K. Madono, M. Tanaka, M. Onishi, and T. Ogawa, “Block-wise scrambled image recognition using adaptation network,” Workshop on AAAI conference Artificial Intelligence (AAAI-WS), 2020.

[24] W. Sirichotudumrong, T. Maekawa, Y. Kinoshita, and H. Kiya, “Privacy-preserving deep neural networks with pixel-based image encryption considering data augmentation in the encrypted domain,” 2019 IEEE International Conference on Image Processing (ICIP), pp.674–678, 2019.

[25] W. Sirichotudumrong, Y. Kinoshita, and H. Kiya, “Pixel-based image encryption without key management for privacy-preserving deep neural networks.” IEEE Access, vol.7, pp.177844–177855, 2019.

[26] W. Sirichotudumrong and H. Kiya, “A gan-based image transformation scheme for privacy-preserving deep neural networks,” 2020 28th European Signal Processing Conference (EUSIPCO), pp.745–749, 2021.

[27] W. Sirichotudumrong and H. Kiya, “Grayscale-based block scrambling image encryption using ycbcr color space for encryption-then-compression systems,” APSIPA Transactions on Signal and Information Processing, vol.8, no.1, pp.–, 2019.

[28] O. Watanabe, A. Nakazaki, and H. Kiya, “A fast image-scramble method using public-key encryption allowing backward compatibility with jpeg2000.” 2004 International Conference on Image Processing, 2004, ICIP ’04, vol.5, pp.3435–3438, 2004.

[29] T. Chuman, W. Sirichotudumrong, and H. Kiya, “Encryption-then-compression systems using grayscale-based image encryption for jpeg images,” IEEE Transactions on Information Forensics and Security, vol.14, no.6, pp.1515–1525, 2019.

[30] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.Y. Fu, and A.C. Berg, “Ssd: Single shot multibox detector,” European conference on computer vision, pp.21–37, Springer, 2016.

[31] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” International Conference on Learning Representations, 2015.

[32] A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, T. Killeen, Z. Lin, N. Gimelshein, L. Antiga, A. Desmaison, A. Kopf, E. Yang, Z. DeVito, M. Raison, A. Tejani, S. Chilamkurthy, B. Steiner, L. Fang, J. Bai, and S. Chintala, “Pytorch: An imperative style, high-performance deep learning library,” Advances in Neural Information Processing Systems, pp.8024–8035, 2019.

[33] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, et al., “Imagenet large scale visual recognition challenge,” International journal of computer vision, vol.115, no.3, pp.211–252, 2015.

[34] M. Everingham, L. Van Gool, C.K. Williams, J. Winn, and A. Zisserman, “The pascal visual object classes (voc) challenge,” International journal of computer vision, vol.88, no.2, pp.303–338, 2010.

[35] M. Everingham, S.A. Eslami, L. Van Gool, C.K. Williams, J. Winn, and A. Zisserman, “The pascal visual object classes challenge: A retrospective,” International journal of computer vision, vol.111, no.1, pp.98–136, 2015.

[36] T.Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C.L. Zitnick, “Microsoft coco: Common objects in context,” Computer Vision – ECCV 2014, ed. D. Fleet, T. Pajdla, B. Schiele, and T. Tuytelaars, Cham, pp.740–755, Springer International Publishing, 2014.

[37] H. Rezatofighi, N. Tsioi, J. Gwak, A. Sadeghian, I. Reid, and S. Savarese, “Generalized intersection over union: A metric and a loss for bounding box regression,” Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp.658–666, 2019.

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