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A study on fire data augmentation from video/image using the Similar-label and F-guessed method

Jong-Sik Kim and Dae-Seong Kang*

Dept. of Electronics Engineering, Dong-A University,37 Nakdong-daero 550 beon-gil
Saha-gu, Busan, Korea
{kjsluke, dskang}@dau.ac.kr

Abstract. When data collection is limited, such as in the case of fire detection, improving the detection rate with only number of small labeled data is difficult. Therefore, researchers have conducted many related studies, among which semi-supervised learning methods have achieved good results in improving detection rates. Most recent semi-supervised learning models use the pseudo-label method. But there is a problem, which is that it is difficult to label accurately in samples that deviate from the true label distribution due to false labels. In other words, due to the pseudo-label used for data augmentation, erroneous biases can be accumulated and adversely affect the final weights. To improve this, we proposed a method of generating Similar-labeled data (prediction result labeling value and correct answer value are similar), which was used through the F-guessed method and the Region of Interest (ROI) expression method in the video during initial learning. This has the effect of preventing the bias from being distorted in the initial stages. As a result, data generation increased by about 6.5 times, from 5,565 to 41,712, mAP@0.5 increased by about 26.1%, from 65.9% to 92.0%, and loss improved from 3.347 to 1.69, compared to the initial labeled data.

Keywords: semi-supervised learning, deep learning, pseudo-labeling, fine-tuning, Similar-label, F-guessed.

1. Introduction

The semi-supervised learning method has developed increasingly in computer vision over the past few years. Currently, the most advanced methods introduce hybrid methods by simplifying previous work or combining them with other formulas in the aspect of architectures and loss functions [1]. However, supervised learning is the most used method in the field of deep learning. Supervised learning is a learning method for memorizing learning patterns. It is not easy to identify data that has never been learned before. A lot of labeled data must be required for better generalization [2]. In addition, obtaining large numbers of labeled data in areas where labeling requires expertise or the labeling process takes a long time may be difficult. To improve this problem, Dong- Hyun Lee proposed a pseudo labeling method [3]. The pseudo labeling method is a simple method that can be used for both classification and regression. But there is a limit to improving performance and challenging to match the correct label if a sample is out of the distribution of the labeled answer [4].

* Corresponding authors

However, numerous Semi-Supervised Learning (SSL) papers inspired by the pseudo-labeling method have been published [5, 6, 7, 8, 9]. Among them, MixMatch [10], ReMix-Match [11] and FixMatch [12] announced by Google tried various methods to supplement the problems of pseudo label. MixMatch is training by applying entropy minimization to labeled and unlabeled data. Unlabeled data is labeled using the pseudo labeling method. Pseudo-labeling is sensitive to parameter tuning as it is a method of combination of various mechanisms. Therefore, it requires careful parameter tuning. Nowadays, semi-supervised learning models are mainly using the pseudo- labeling method. When pseudo labels are used, incorrect bias will be stacked due to the pseudo labels. If not solving the data bias, it will learn a biased decision boundary of a specific data sample unlikely the actual labeled data. It can be complicated to use current methods when there are constraints on labeled data, such as in the case of a fire event. Sometimes, there may be errors in recognizing data if it was not included in the learning data. This means that the collected answer label data distribution may not be able to cover all the data.

In this paper, we suggested the following ways to minimize data bias when collecting the data. Instead of the pseudo-labeling method, apply the Similar-labeling method, which uses Region of Interest (ROI) on a video to get labels which are close to the answer. To classify no correct answer label data more precisely, using guessed label after fine-tuning the existing method. Instead of learning all the data at once, extracting guessed labels from half quantities (2,187 pcs) of the initial data (5,565 pcs) and using the extracted data for the next step learning model. To improve the fire recognition rate and significantly reduce the time required for human labeling by minimizing the training bias in several steps. Fig. 1 is a diagram of fire data creation that extracts Similar-label by setting the ROI of suggested algorithms and using Intersection Over Union (IOU) comparison.

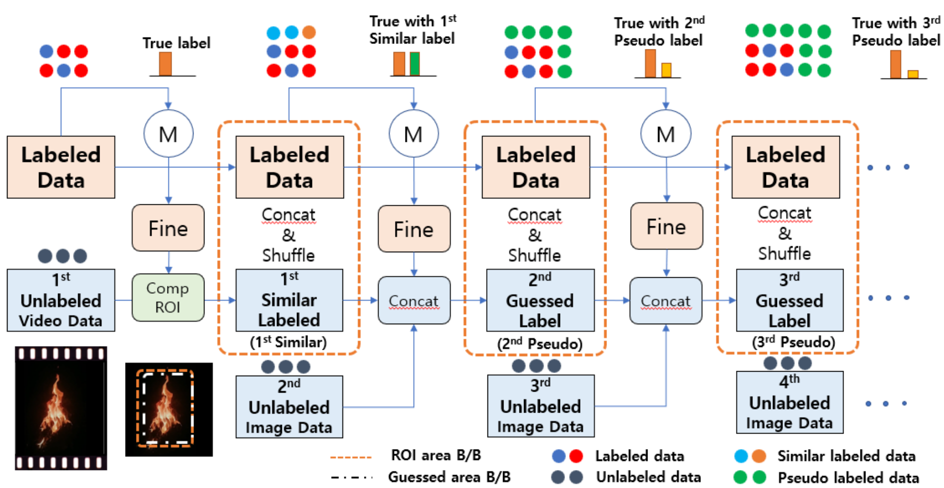

Fig. 1. Conceptual diagram of fire data augmentation using Similar-label and F-guessed comparison method

2. Related work

Semi-supervised learning can be considered if there are few correct answer-labeled data and many labeled data without correct answers. Semi-supervised learning aims to improve performance by applying supervised learning for a few correct answer labels and applying Unsupervised learning for many labeled data without correct answers. Various semi-supervised learning methods have appeared from the perspective of using labeled data without answers for learning. Semi-supervised learning has emerged to collect correct answer data and reduce the resources and costs for labeling work. Objective Function of semi-supervised learning can be expressed as minimizing the sum of supervised learning loss Ls and unsupervised learning loss Lu as in equation (1).

$$Loss = Ls + Lu \tag{1}$$

Semi-supervised learning can be seen as modeling the essential characteristics of the data itself, moving away from the model of the correct answer of the label. It means that the generalization performance can be improved with a small number of learning through a small number of true-label data. Studies similar to the currently proposed technology include pseudo-labeling, MixMatch and FixMatch.

2.1. Pseudo-labeling

Pseudo-label is a popular method because it is very simple. Based on the predicted values of the models sufficiently learned by supervised learning, we attach pseudo-label to the unlabeled data with simple rules such as threshold. The model is then re-learned by combining labeled data and pseudo-labeled data [5]. Fig. 2 shows the basic concept of the pseudo-label method very well.

2.2. MixMatch

Recently, semi-supervised learning algorithms get supervised loss for labeled data and unsupervised loss for unlabeled data. A method of learning a model using these two losses is widely used. Entropy minimization, Consistency loss and MixUp methods were suggested for Unsupervised loss. MixMatch is a supervised learning algorithm that encompasses the three methods. In Fig. 3 shows the MixMatch operation.

- Entropy minimization: The classifier minimizes the predictive entropy of labeled data without an answer, and one of the methods of entropy minimization is pseudo-labeling.

- Mixup: Mixup is a method that mixes augmented answer labels and without answer labels and overlaps the answer and without answer labeled data images for the data.

- Consistency regularization: Using answer labels and without answer labels for learning the data. When similar or modified data are offered to learn, the result has to present similar results.

The algorithm performed better than existing semi-supervised learning algorithms even when using only a small number of labeled data. When correct answer labeled data (X) and labeled data without answers (u) provide for the MixMatch algorithm, it will

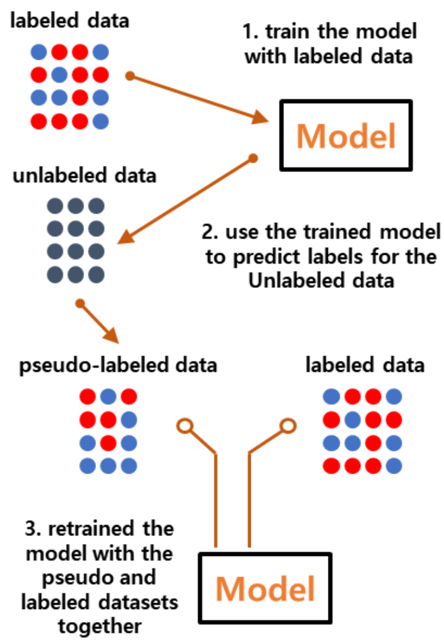

Fig. 2. Pseudo-labeling operation

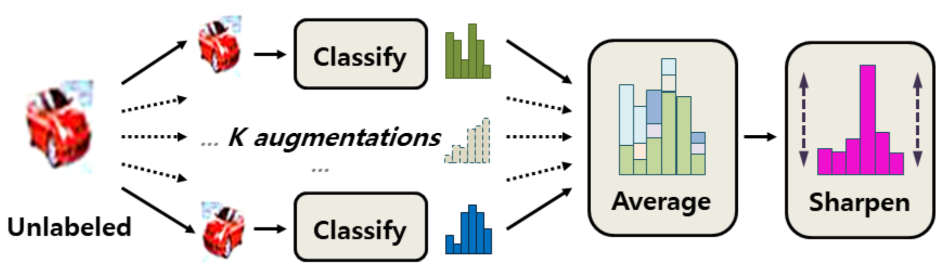

Fig. 3. MixMatch operation

generate processed answer labeled samples ($X^{'}$) and predicted guessed labeled ($u^{'}$). Officially, coupling loss L for semi-supervised learning is defined as equation (2) [10][11].

$$\begin{aligned} X', u' &= MixMatch\left(X, u, T, K, a\right) \\ Lx &= \frac{1}{|X'|}\sum_{xpeX'} H\left(P, Pmodel\left(y|x;\theta\right)\right) \\ Lu &= \frac{1}{L|u'|}\sum uQeu'||q - Pmodel\left(y|u;\theta\right)||_2^2 \\ L &= Lx + \lambda uLu \end{aligned} \tag{2}$$

H(p, q) is the cross entropy between distributions p and q, and T, K, α, λu are hyperparameters.
T : sharpening temperature.
K : number of unlabeled augmentations.
α : Beta distribution for MixUp.
λu: unsupervised loss of weight.

2.3. FixMatch

FixMatch is a method of training a supervised learning model from correct answer-label images using cross-entropy loss. To get two images by applying weak and strong augment methods for each image of labels without a correct answer. Weakly augmented images are passed on to the model, prediction for the class is obtained, and the probability of the most confident class is compared to a threshold. Use the class as the basic label (pseudo-label) if it is higher than the threshold. After that, strongly augmented images are passed on to the model and proceed with predictions for the class. The predictions can be used as cross-entropy loss to compare with the answer pseudo-label. At this point, combining two losses and optimizing the model. In Fig. 4, the FixMatch Realization method is schematized [12].

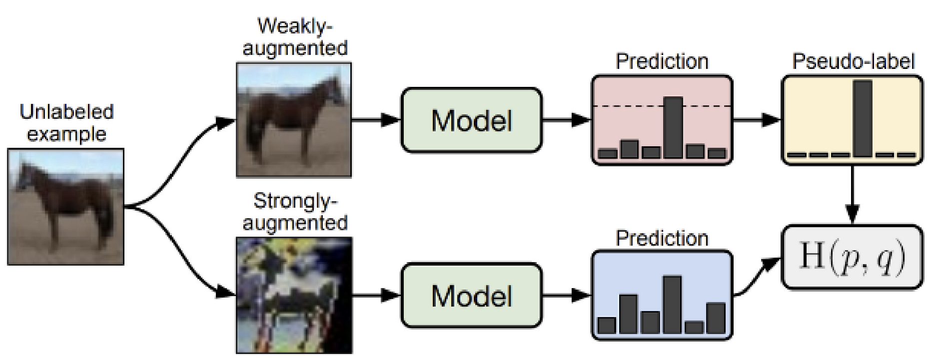

Fig. 4. FixMatch operation

2.4. Fine-tuning

Fine-tuning transforms an architecture to fit image data for new purposes based on previously learned models and updating learning from already learned model weights. In deep learning, fine-tuning means injecting additional data into the existing model to update parameters. For more detail, fine-tuning can be considered as precise parameter tuning. To finish the Fine-tuning, the existing learned layer data must be additionally trained to update the parameters. If it uses completely random initial parameters or a less abstracted layer that learns general features, this will collapse the entire parameters because of overfitting. To change the purpose of the pre trained model for needs, fine-tuning is required with one strategy from four strategies in Fig. 5 [13].

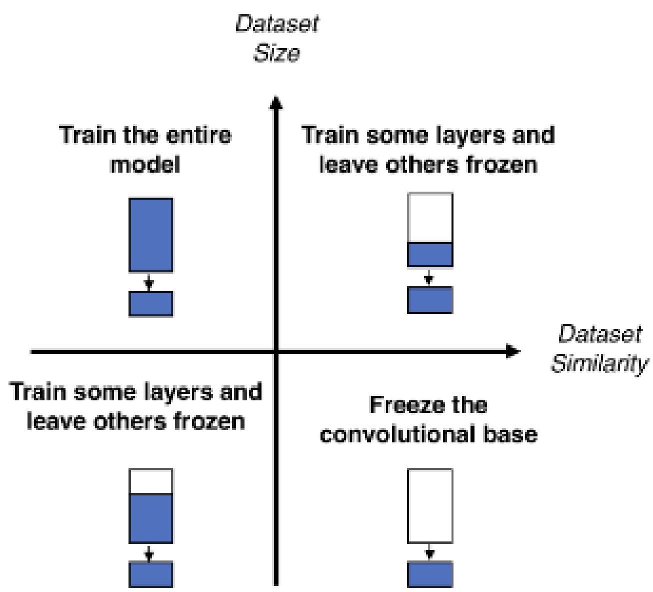

Fig. 5. Types of fine-tuning

The first quadrant is a big dataset but differs from the pre-trained model dataset. Because the dataset is big, the dataset can train a model from the beginning and proceed with all works. The second quadrant uses a big dataset similar to the dataset of the pre-trained model. Since the dataset is large, overfitting will not be an issue and can be learned effectively. The third quadrant uses a small dataset which is opposed to the dataset of the pre-trained model. It is hard to find a balance between the quantity of trainable layer and the same amount of layer, and it could be overfitting. The fourth quadrant is the small dataset but uses all the pre-trained models' datasets. This method changes only the last Fully Connected (FC) and trains a new classifier [14].

3. Proposal method

As mentioned in the introduction, the weakness of the pseudo-label is when the learning model is overfitted to one side and has a bias, and the bias is also applied when generating the pseudo-label. In other words, since the weights are shared, learning through potentially false pseudo-labels is risky. In case of limited data collection, such as fire, it is inevitable to have more distorting bias. In addition, " A Study on Fire Data Generation and Recognition Rate Improvement using F-guessed and Semi-supervised Learning " previously studied by the author [15] is also a model trained by the pseudo-labeling method. Which extracts images per frame from fire videos and uses fire pseudo-labeled, so overfitting to one side, we had no choice but to have the bias accumulated.

3.1. Similar-labeled data using ROI

In this study, the Region of Interest (ROI) was set in the Fire image to prevent false biases from being included in the weights during initial learning. When generating F-guessed, the decision boundary detected within this ROI area obtains the pseudo-labeled data most similar to the labeled data (correct answer or true label). In other words, since the existing pseudo-label data utilizes an unlabeled dataset, it is impossible to know how much wrong bias it has for which class because there is no label information [12]. However, Similar-labeled data has the most similar class and decision boundary to the labeled data. Fig. 6 shows a process of setting an ROI using unlabeled video and extracting Similar-labeled data. For more details, set the ROI for the fire part in the video images and calculate the IOU of the decision boundary (B_d) and boundary of ROI (B_{ri}), occurring near the ROI. If the difference is less than 50%, use for Similar-labeled data. Equation (3) shows the calculation method.

$$B_d \, and \, B_{ri} \, of \, IOU = \frac{\mathrm{B}_d \cap B_{ri}}{\mathrm{B}_d \cup B_{ri}} \tag{3}$$

And as shown in Fig. 7, a fire gradually increases over a certain period when it is ignited. This means that the shape of the fire will vary as long as the camera is not moving, but the size of the fire will remain similar to its size until the fire expands. Based on this, when extracting a decision boundary from a fire video, set ROI on the video of the fire point. Until the fire expands significantly, the shape and form of the fire mostly change within these ROIs. As a result, gathering a considerable amount of fire data similar to labeled data without the need for separate labeling tasks each time is possible.

The disadvantage of this study is that the Region of Interest (ROI) must be drawn once on the fire image. However, the initial ROI display has more advantages than disadvantages in improving overfitting due to incorrect fire labeling in a state with little fire-labeled data at the beginning of learning. In this study, relabeling was performed closer to labeled data to minimize mislabeling that may occur when the number of true labeling data is small. As a result, a similar labeling technique improved the recognition rate to minimize misrecognition when predicting fire image data.

3.2. Fine-tuning

The reason for applying fine-tuning is to transform the architecture to suit the image data for a new purpose based on the previously learned model and to update the learning from

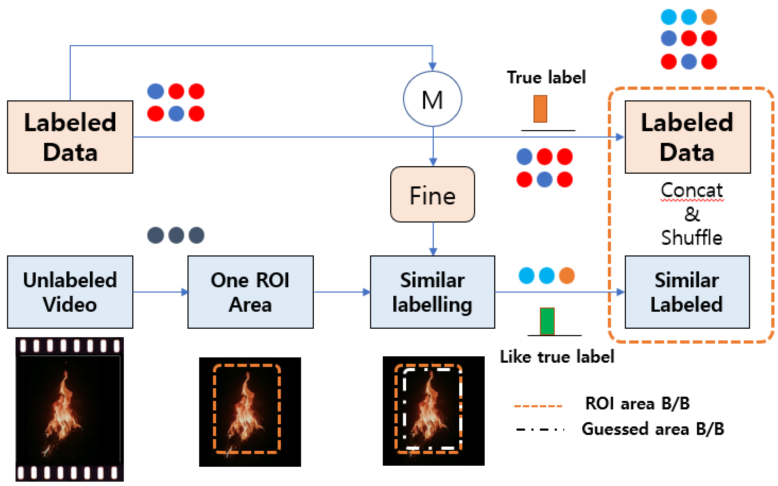

Fig. 6. Conceptual diagram of initial fire data generation using Region of Interest (ROI) comparison method

Fig. 7. The shape and size of fire in the ROI(Region of Interest) in the video

the already learned model weights. The parameters of the less abstract layer that learned the general features were added to prevent overfitting. An optimization process is added by learning a previously learned layer and updating parameters. Fine-tuning means re-learning and optimizing processes using existing neural networks. This is because labels that are more similar to the true labels can be predicted if label data without correct answers is predicted(guessed) after precise parameter tuning of the existing learning model [13].

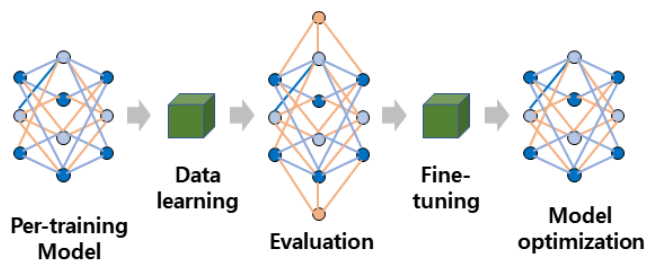

Fig. 8. Fine-tuning optimization method

Fig. 8 shows an optimization method through fine-tuning. It is designed to perform additional fine-tuning each time new data is added, and a new prediction model is created by re-mixing the existing labeled dataset, similarly labeled dataset, and guessed labeled dataset using the additional fine-tuning learning result.

3.3. Step-by-step data growth and redundant labeling

Instead of learning all data at once, it is a method of extracting a guessed label with about half the quantity (2187 pcs) of the initial labeled data quantity (5,565 pcs) and using it as the next step of the learning model. The label was continuously increased by about half its initial quantity. This is because the training process is divided into stages to minimize initial overfitting [7]. Also, the initial labeled data (true label) was used only for learning purposes and was not used as F-guessed data. In other words, for semi-supervised learning, labeled data is always used only as learning data (labeled data) regardless of the learning order, and no transformation is made by labeling. Unlabeled data and Similar-labeled data are designed so that final prediction labeling is always applied according to the learning order for semi-supervised learning. It means the true label + prediction (guessed + similarity) data combines and mixes the true label and the correct answer prediction label to create a new step model for semi-supervised learning. A new fine-tuning is performed using this learning weight value [8]. Fig. 9. is a conceptual diagram for redundant labeling.

4. Experimental Results

A research experiment on how to generate fire data from a video using the F-guessed method was conducted in a computer environment with CPU: AMD Ryzen 7 3700X 8-

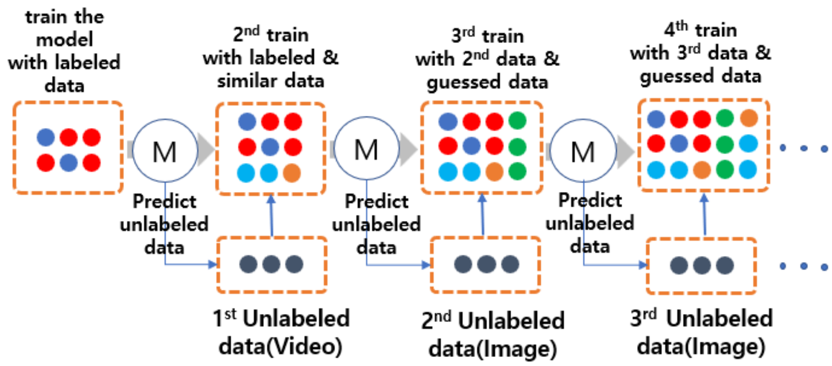

Fig. 9. Conceptual diagram of step-by-step data increase and redundant labeling

Core Processor 3.6 GHz, GPU: NVIDIA GeForce RTX 8000, and 32GB of RAM. Moreover, CNN used Darknet 53, and an object detector has experimented with yolov4 [16]. Table 1. shows the initial labeled dataset information. The numbers in this table mean the number of images, and even in the actual fire image, Person, Smoke, and Spark also include a considerable number of overlapping labels depending on the image. In addition, these images secured data using the Internet [17], fire department site photos, and self-data augmentation methods (Using its own DA-FSL augmentation method [18]).

Table 1. Basic labeled data set information.

Data	Fire	Person	Smoke	Spark	Total
Q'ty	2585	1500	634	846	5565

As shown in Table 1, the experiment was conducted to determine the impact of false bias on pseudo-label during learning when there is not enough initial data. Fig 10 shows false labeling image results from an experiment using unlabeled video data.

To prevent false bias from being included in the weight when initial learning data is insufficient, a region of interest (ROI) was marked on the fire video to obtain pseudo-labeled data most similar to the labeled data when generating pseudo labels. Then, the decision boundary detected within the ROI area was checked to exclude incorrect Labeled data or change Labeling to secure Similar labeled data that was most similar to the correct answer. Since the existing pseudo-label data uses an unlabeled dataset and does not have labeled data information, it was hard to know how much incorrect bias it had for which class. However, Similar labeled data has the most similar class and decision boundary to labeled data using the ROI method.

Table 2 shows the quantity of data augmentation and total image quantity at each stage of fire data generation using the Similar-label and F-guess method. 5,565 pcs correct answer labels used in the initial learning are labeled by humans (labeled data). Similar labeled data close to the correct answer labels were generated using the ROI in the video.

Fig. 10. Red color B/B indicates ROI, Top Left (TL) image is incorrectly recognized as a spark, Top Right (TR) image is incorrectly recognized as Fire and Person, and Bottom Left (BL) image is Fire and Person. In the case of Bottom Right (BR) images, it is mistakenly recognized as smoke

By using the unlabeled data images, table 2 shows the F-guessed quantities guessed by the labeled data. F-guessed quantity increases as it repeats its steps with the final weight values obtained from F-guessing, learning, and labeling on video/image. Except for existing labeled data, added Unlabeled data will repeat learning and labeling in every step. Minus numbers in F-guessed columns are numbers of deleted images with no label in labeling steps.

Table 2. F-guessed labeled data set augmentation information

Data	Labeled Q'ty	Unlabeled Q'ty	F-guessed Q'ty	Division
Basic labeled data	5,565	0	0	image
1st augmentation	5,565	2,783	2,783	Similar label(video)
2nd augmentation	5,565	4,175	6,956	image
3rd augmentation	5,565	6,261	12,976 (-242)	image
4th augmentation	5,565	9,391	22,609 (-416)	image
5th augmentation	5,565	14,087	36,696 (-548)	image

In Table 3, the results of the change in fire recognition rate over five times by applying the Similar-label and F-guess method based on the learning model of the initial answer labeled data are displayed in the order of Loss, mIOU, and mAP. Compared to the initial correct label data, Loss decreased by up to 1.66%, mIOU increased by 26.6% and mAP@0.5 improved by 27.1% as a result of the test. Additional learning was not conducted after the fifth round because the standard for finishing the program was set based on a small change in loss. It was judged that the low loss meant that the consistency of the labeling data was secured.

Table 3. Object precision rate test results based on max batch = 8,000.

Mode		Loss(%)	mIOU(%)	mAP(%)
Basic labeled data (True labeled)	Train	3.347	52.23	65.93
	Fine-tuning	3.060	56.12	70.67
1st augmentation (Similar labeled)	Train	2.783	56.35	67.48
	Fine-tuning	2.63	59.64	75.42
2nd augmentation (F-Guess labeled)	Train	2.70	65.88	75.03
	Fine-tuning	2.413	65.53	77.22
3rd augmentation (F-Guess labeled)	Train	1.958	69.33	78.7
	Fine-tuning	1.828	70.09	79.30
4th augmentation (F-Guess labeled)	Train	1.66	73.44	87.00
	Fine-tuning	1.516	76.16	87.45
5th augmentation (F-Guess labeled)	Train	1.815	76.57	90.67
	Fine-tuning	1.69	78.84	92.0

Fig. 10 shows the effect of the wrong bias on pseudo labels during learning with a lack of primary learning data. And Fig. 11 compares and displays the results of the labeling image that has changed since applying F-guessed with Similar-labeled data. In more detail, the initial learning model learned with early primary labeled data inevitably results in mislabeling, which in turn causes misrecognition. Therefore, to minimize erroneous labeling at the beginning of learning, the program was modified to exclude images for erroneous labeling within the Region of Interest (ROI) or automatically change them to fire classification labels. This proposed method is named similar labeling because it re-labels similar to the correct answer. As a result, the mislabeling that occurs in Basic labeled data is significantly improved after using Similar-labeled data, as shown in Fig. 11.

In Fig. 12, each stage's change in fire image recognition rate is displayed from 1st to fifth. The image data used for each order results from testing by randomly selecting general images not used for learning from the Internet. The result shows many things that could be improved when initially proceeding with a small number of labeled data. However, it shows stable results as the additional labels continue to increase. Then, only the images showing the greatest difference among several images were selected.

Image No.1 identified fire correctly but kept changing the smoke direction during the learning processes. Image No. 2 correctly identified fire but struggled with recognizing smoke at first. However, through the learning process, it improved recognition precisely over time by smoke and clouds. Image No.3 also recognized fire correctly and smoke kept changing through the learning process. Initially, fire recognition was accurate even with a small amount of data. However, due to limited data, both misrecognition and unrecog-

Fig. 11. Comparison of labeling image results changed after applying Similar-labeled data and F-guessed

nition occurred. However, increasing the data using the F-guessed method resolved these issues.

Table 4 presents the experimental results for ”F-guessed” and ”Similar-label and F-guessed”. The results are based on 36,749 manually labeled labels by humans and 5,565 initial answer labels. Comparing manual labeling with Similar-label, the result improved Loss by 0.69, mIOU by 9.42% and mAP by 13.66% as a result. Also, compared with the existing F-guessed method, Similar-label improved performance considerably.

Table 4. Manual labeled, F-guessed and Similar-labeled data comparison experiment tables

Data	Q’ty	Loss(%)	mIOU(%)	mAP(%)
Basic labeled data	5,565	3.347	52.23	65.93
Manual labeled	36,749	2.38	69.42	78.34
F-guessed labeled	35,633	1.41	78.22	82.49
F-guessed + Similar-labeled	41,712	1.69	78.84	92.0

In comparison to the previously studied F-guessed labeled method, incorrect bias significantly affects the recognition rate improvement in the initial stages. However, the Similar-labeled method enhanced recognition rate accuracy by approximately 10% compared to the present method.

5. Conclusions

In this paper, if data collection is limited, such as in a fire or disaster, the paper proposes a Similar labelling method to improve recognition rates when only a small amount of labeled data is available. The current pseudo-labeling method has limitations in improving performance because it is difficult to accurately label samples that are out of the distribution of correct labels. Therefore, a method of marking a Region of Interest (ROI) in a fire video was used to prevent false biases from being included in the weights during initial learning. This is method automatically changes to a fire class label when the decision boundary detected within the ROI area is recognized as an incorrect class label when the initial pseudo label is created. In this way, Similar-labeled data most similar to the true labeled data can be obtained. As a result, loss decreased by up to 1.66% compared to the initial basic label data, mIOU increased by 26.6%, and mAP@0.5 improved by 26.1%. Also, the number of secured data was 41,712 F-guessed data, which increased by 6.5 times based on the initial true label data of 5,565. And, through additional research in the future, we plan to further study the false recognition rate of fire through uncertainty distribution by using the Bayesian Neural Network to improve false recognition of fire.

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Fig. 12. Comparison of labeling image results changed after applying Similar-labeled data and F-guessed

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Jong-SiK KIM received the B.S. in Electronic Engineering from Pukyong National University, South Korea, in 1991; received his master's degree in electronics engineering at Dong-A University, South Korea, in 2020; currently as a doctoral student in Department of Electronic Engineering at Dong-A University; His current research interests Image processing and AI.

Dae-Seong Kang (Corresponding author: dskang@dau.ac.kr) received his Ph.D. in electrical engineering at Texas T&M University, USA, in 1994; He is a professor at electronics engineering in Dong-A University; Main research directions: Image processing, pattern recognition and machine learning.

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