# Deep Learning-based Defect Detection on Livestock Operations

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## ABSTRACT

The recent growth of computer vision system research has contributed to the advancement of livestock operations including meat processing. However, the defect detection of livestock products has not been actively studied due to the scarcity of dataset despite its significance. In the real world, the ratio of the defects in the livestock dataset is extremely low, compared to the normal products, resulting in insufficient model training. To address this problem, this study propose a deep learning-based anomaly detection method for an extremely imbalanced dataset. Adopting an anomaly detection framework from prior research, we suggest an adversarial autoencoder, which includes loss inversion to optimize reconstruction error for training skewed data, and a linear perturbation method called the Fast Gradient Sign Method (FGSM) to generate noises as anomaly cases. The model was then evaluated on the real-world dataset acquired from a livestock factory to detect defective chicken carcass (e.g., broken leg, injured skin, bent wing). The experiment results show that the proposed model outperforms existing models used for anomaly detection problems (i.e. DevNet and DeepSAD) and loss inversion and FGSM successfully improve the model performance when detecting livestock defects, even if the dataset contains extremely few defects.

## CCS CONCEPTS

• **Computing methodologies → Anomaly detection**; • **Applied computing → Agriculture**.

## KEYWORDS

Neural Networks, Autoencoder, Anomaly Detection, Livestock Quality Control, Image classification


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## 1 INTRODUCTION

Machine Learning (ML), which is a subset of artificial intelligence (AI), is changing every field of the modern world, and livestock operation is not an exception [23]. Applications of computer vision are growing in importance in livestock systems due to their ability to generate real-time, non-invasive, and accurate animal-level information [17]. However, much research effort has been focused on automatic image analysis for body parameter estimation (e.g. weight, height) of livestock [4]. On the other hand, the visual defect detection of livestock was not a frequently studied area even though it is important for quality control and business revenue.

Defect detection in agriculture is a challenging and important issue [6]. Empowered by recent image processing technology, visual defect detection has been actively applied and now harvesting optimistic results [10]. Yet, the livestock domain has been far behind due to the lack of datasets designed especially for use in livestock computer vision systems [17]. Moreover, many real-life applications, such as livestock production, suffers from the data imbalance issue as there are only a few pieces of defective product data available. Also, there are naturally challenging conditions where it is very difficult for defect detection methods to differentiate between defective and normal status images [8]. To address these issues, this study proposes a deep learning-based visual defect detection framework suitable for dealing with an extremely imbalanced livestock dataset. To handle the extremely skewed ratio in data labels, we adopt prior research related to anomaly detection, which includes reconstruction error optimization and adversarial attack.

The rest of this article is organized as follows. In Section II, the prior studies related to visual defect detection and anomaly detection are explained. In Section III, the proposed framework for defect detection is illustrated and as well as the experiment setting. In section IV, the experimental results are presented and the implications are discussed. Then section V concludes this article.

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# 2 RELATED WORK

## 2.1 Visual Defect Detection

*2.1.1 Defect Detection Based on Deep Neural Network.* Over the last decade, deep learning has earned a remarkable reputation in the image recognition domain. The architectures and algorithms for the visual object detection models such as Region-based CNN (convolutional neural network), YOLO (you only look once), SSD (single shot detector), and cascaded architecture have been introduced with great potential in automatic defection detection area [26]. These models have been widely adopted especially in detecting defects in manufactured products. A representative area is to detect tiny flaws in the product surfaces [9, 14]. By utilizing deep neural network models, these studies have proven the effectiveness of automated visual defect detection while expanding the detection targets to further strengthen their utilities.

*2.1.2 Visual Defect Detection in Agricultural Sectors.* The domain of agriculture is one of the fields where visual defect detection is flourishing. The detection of diseased (or spoiled) fruits and vegetables has been the main research subject [6]. Similar to defect detection in mass production, CNN based detection models have been utilized to detect defects such as bruises, contamination spots, pathogen infections, and chilling injuries [3, 5, 28]. However, the detection of livestock defects has been out of research focus, despite the increasing demands for visual detection in livestock operations. Most image-based livestock production studies have focused on automatic image analysis for body parameter estimation (e.g. weight, height) of livestock and detecting animal behaviors [4, 17]. As livestock production has been transitioning to mass production, the necessity for visual detection is getting much attention [2]. Therefore, further research effort on visual defect detection on livestock products is much warranted.

*2.1.3 Challenges in Livestock Defect Detection.* As stated above, visual defect detection for livestock goods is a less-explored research area. The most challenging issue is the lack of a dataset. There are only a few livestock public datasets designed for computer vision research and their purpose is limited to detecting animal bodies and estimating body size [17]. Moreover, defect detection is a complex real-world problem because only a small proportion of defects occur compared to normal cases [22], implying that the extreme class imbalance problem in the dataset should be considered for visual defect detection. Yet, prior research utilized datasets with relatively high or even balanced proportions of defects. As a result, their application is limited in cases where defective data is scarce.

## 2.2 Imbalance Problem in Defect Detection

*2.2.1 Detecting Anomalies.* In this research, the concept of anomaly detection (AD) is adopted to tap the imbalance problem in livestock defect detection. In real-world scenarios, it is difficult to obtain defect data primarily due to their scarcity and variety. Thus, researchers have tried to set the problem as anomaly detection, which tries to solve the task of detecting data or events that are very scarce or even do not exist in the training data [16]. There are various types of detection techniques. Among the taxonomy of deep anomaly techniques proposed by Pang et al. [18], we aim to explore the techniques suitable for the livestock defect detection problems originating from data imbalance issue: data-efficient learning and noise-resilient anomaly detection.

*2.2.2 Data-efficient Learning of normality.* Practically, it is difficult and costly to collect large-scale labeled anomaly data that the model should learn with a dataset that includes only a few anomaly data [18]. Consequently, it is often suggested to use readily accessible labeled data as much as possible. Also, to maximize the utility of limited anomaly data, the techniques that capture and represent the differences between normal and abnormal have been used in popularity. One of the most popular examples is to set anomaly scores based on one-class classification. This technique assumes that all normal cases come from a single class and can be summarized or learned by a model, to which anomalies do not fit well [18]. The representative works for the one-class classification-based model are DeepSVDD and DeepSAD proposed by Ruff et al. [20, 21]. DeepSAD is a generalization of the unsupervised DeepSVDD method that utilizes a pre-trained encoder model to train mostly normal data to optimize the model to a representative center in hypersphere space based on the reconstruction error. Hence, the deviated samples are considered anomalies. Another representative work in one-class classification is DevNet proposed by Pang et al.[19]. Their model leveraged a few labeled anomalies and introduced end-to-end learning of anomaly scores by neural deviation learning. By adopting adversarial learning to one-class classification, the model estimates and synthesizes the anomalies, while all normal instances are summarized by a discriminative model. The aforementioned models are very intuitive, easy to implement, and high in performance. However, they are vulnerable to the data noise and the generated anomaly representation may not be suitable for the dataset (or situation) with extremely few anomalies [27].

*2.2.3 Noise-resilient Anomaly Detection.* As briefly explained in the prior subsection, anomaly detection models can be vulnerable to noisy instances that are mistakenly labeled as an opposite class label or less deviated from a threshold [18]. Prior studies also tried to address such issues by adding noise data or perturbed samples so that the robustness of the models could be enhanced. Such techniques are called adversarial attacks. There are several examples of adversarial attacks presented in prior research. Goodfellow et al. [7] pioneered to address the issue in the deep-learning research by proposing a simple linear perturbation method that can easily fool models by increasing the loss function, called Fast Gradient Sign Method (FGSM). Since then, various adversarial attack techniques have been presented by utilizing Gaussian distribution [13], selective and iterative gradient sign method [29], and hardened variant samples [25].

# 3 DEVELOPING LIVESTOCK DEFECT DETECTION MODEL

## 3.1 Overall Architecture

To address the imbalance data issue in livestock defect detection, we propose a new model, built upon a one-class classification-based model, that uses an adversarial attack as in Figure 1. In particular, we apply loss inversion to reconstruction loss using a one-class classification model, which includes convolutional block, autoencoder, and discriminator, to detect anomalies more effectively in

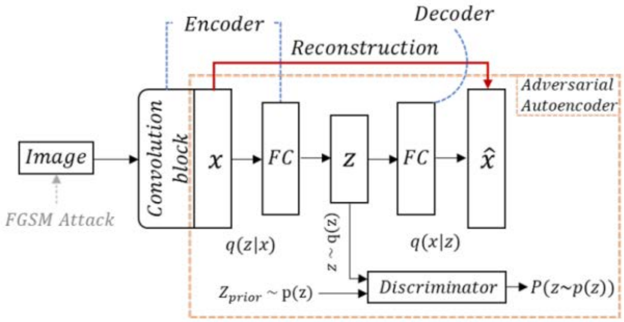


**Figure 1: Proposed livestock defect detection model architecture**

dealing with confusing image data. Reconstruction loss is not applied to original data but on the feature vector from the convolution block [11], which relieves the burden of reconstructing the entire input image. For reconstruction error, loss inversion was applied to further increase the loss in the case of anomaly. In addition to that, we generate anomalies, as an adversarial attack, using FGSM and treat them as unseen anomalies to ensure the robustness of the model. The following sections provide detailed information about each of the components.

## 3.2 Convolutional Block

The convolution block in the encoder consists of all blocks of the classification head from a CNN model. When the input image passes through the convolution block, a one-dimensional vector, $x$, is returned. Then, reconstruction is conducted on $x$ [11], using an adversarial autoencoder [15]. The reason we do not reconstruct the original input image is to avoid reconstructing irrelevant or unimportant parts, and most importantly, to reduce the burden of reconstructing the entire input image. Another way is by masking the interesting pixels and calculating the error using the masked pixels of the input image. However, it is a bit complicated and time-consuming. By constructing the feature representation $x$, there is no need to consider these inconveniences.

To fully exploit the feature vector for anomaly detection with the reconstruction method, the feature vector should involve discriminative representation that is comparable to the original image. Hence, we adopt the convolutional block from a CNN model, instead of shallow blocks like convolutional autoencoders, to extract useful feature information.

## 3.3 Reconstruction Error

In this study, we presume that it is difficult to distinguish the characteristics of livestock defects from those of normal products. Through an autoencoder, anomalies were attempted to be detected through reconstructed images to better understand the confusing images. A variational autoencoder (VAE) is usually used to detect anomalies by creating samples based on the distribution of normal data. When anomaly data is introduced to VAE, it deviates from the learned distribution, resulting in a larger reconstruction error that is used to detect anomalies. This VAE assumes the learned prior distribution as a gaussian distribution. However, in our setting, we train both normal and anomaly data so that these two latent vectors can have distinct distributions respectively. This study, therefore, uses an adversarial autoencoder (AAE) rather than a VAE, as it can be applied to any prior distribution [15].

**Algorithm 1** Livestock Defect Detection

MSE: Mean Squared Error
CB : Convolution Block
D : Discriminator
En : Encoder
De : Decoder
**for** $i = 1$ to $n_{epoch}$ **do**
    **for** $j = 1$ to $n_{batches}$ **do**
        $x \leftarrow CB(X)$
        $z \leftarrow En(x)$
        $x_{recon} \leftarrow De(z)$
        $Loss \leftarrow MSE(x, x_{recon})$ ▷ Reconstruction error
        **if** $x_{recon}$ is *anomaly* **then**
            $Loss+ = \lambda/(MSE(x, x_{recon}) + 1e-6)$ ▷ Loss inversion
        **end if**
        $r \leftarrow RandNum(0, 1)$
        **if** $r <= 0.1$ **then**
            $perturbed \leftarrow FGSM(X)$ ▷ FGSM attack to normal sample
            $x' \leftarrow CB(perturbed)$
            $z' \leftarrow En(x')$
            $x'_{recon} \leftarrow De(z')$
            $Loss \leftarrow \lambda/(MSE(perturbed, x'_{recon}) + 1e-6)$
        **end if**
        $x \leftarrow CB(X)$
        $z \leftarrow En(x)$ ▷ Generator
        $n \leftarrow GaussianNoise$
        $D_{Loss} \leftarrow -1/m \sum_{i=1}^{m} log(D(z)) + log(1 - D(En(n)))$
        $G_{Loss} \leftarrow -1/m \sum_{i=1}^{m} log(D(En(n)))$
    **end for**

## 3.4 Loss Inversion

DeepSAD performs training by increasing the distance between the anomaly data and $C$, which is obtained through the pretraining process and is taken as the average of the presentations of the initial forward pass of the normal data. The loss inversion term is also added to the DeepSAD model to measure the distance from $C$ to the labeled anomaly samples. Inspired by this idea, we apply the loss inversion to the reconstruction error and define it as

$$\min_{\theta} \frac{1}{n} \sum_{i=1}^{n} \|x_i - \hat{x}_i\|_2^2 + \frac{2}{m} \sum_{i=n+1}^{n+m} (\|x_i - \hat{x}_i\|_2^2)^{-1} \quad (1)$$

where $n$ are normal samples and $m$ are anomaly samples. While $x_i$ is the $i$-th feature vector from the convolution block and $\hat{x}_i$ is $i$-th reconstructed feature vector from the adversarial autoencoder. The second term of the Equation 1 is the loss inversion for anomalies. It is designed to minimize the loss inversion term by training the model. As a consequence, the reconstruction error of anomaly data will increase. In addition, for anomaly-like data, the reconstruction error would be large enough to help distinguish between normal and anomaly data.

## 3.5 FGSM for Unseen Anomaly

In FGSM, the samples are made in such a way as to increase the loss so that it is difficult to classify. This attack can be applied through a simple linear perturbation. We apply this attack to normal data to generate unseen anomalies, which are difficult to predict as normal. The new unseen anomaly is generated by

$$x_{new} = x_n + \epsilon sign(\triangledown_x J(\theta, x_{recon}, x)) \tag{2}$$

where $x_n$ denotes original input and $x_{recon}$ denotes reconstructed $x_n$ by the autoencoder. The $J$ function means reconstruction loss and $\theta$ means the weight of the model. If the gradient of $J$ is obtained and then the sign function is applied to it, the attack value is simply derived. The degree of attack is determined by $\epsilon$, which is a hyper-parameter. In the case of Gaussian noise, which is commonly used for attack, two parameters, $\mu$ and $\sigma$, must be optimized. However, FGSM can be optimized faster because there is only one parameter. When training these samples, the model makes predictions in the direction of increasing loss.

In the model training, the FGSM attack is applied to the normal data to create perturbed samples, which are then labeled as anomalies. These samples are fed into the encoder to train the model. The attack is applied directly to the input image, and when performing one epoch, the model is trained on the original data and then on the perturbed samples. In order not to generate too many perturbed samples, random numbers between 0 and 1 are generated. The FGSM attack is then applied only when the random number is less than 0.1. The algorithm for our proposed model is presented in the form of pseudo-code in Algorithm 1.

# 4 EXPERIMENT

To assess the performance of our proposed model architecture, we conducted an experiment to compare the performance of our proposed model against the performances of the anomaly detection models from prior research (i.e., DeepSAD, DevNet). We assessed the performances of the models with the CIFAR-10 dataset and the chicken carcass image dataset collected from a food factory in South Korea. After comparison, we conducted an ablation study to examine the effect of implementing loss inversion and FGSM attack. We describe the model implementation setting and datasets below.

## 4.1 Experiment setting

*4.1.1 Model Implementation.* To compare the performance of our model against the performances of the existing one-class classification-based models, DevNet [19] and DeepSAD [21] were implemented. Similar to the proposed model, DevNet is based on semi-supervised learning using limited labeled anomaly data information. Because the focus of DevNet is on anomaly score learning for easy interpretation instead of feature representation learning, the power of learning sufficient representation is deemed not enough. Thus, oversampling for a few anomaly data was required to improve the performance. As for DeepSAD, it detects anomalies through the distance metric based on the value of $C$. Given that our model applies the loss inversion of DeepSAD to the reconstruction loss, we need to check what kind of performance difference it shows from the loss based on the distance metric. In addition, we should check the performance of loss inversion by comparing it with DevNet. For the comparison models and our proposed model, we used pre-trained VGG19 [24] on ImageNet as the backbone of convolution blocks and followed the implementation guidelines presented in prior research [19, 21]. The detailed hyper-parameter settings are presented in Table 1.

**Table 1: Hyper-parameters Settings**

| Parameter | Proposed Model | DevNet | DeepSAD |
|---|---|---|---|
| Epoch | 200 w.ES[a] | 200 w.ES | 200 w.ES |
| Input Size | 448x448 | 448x448 | 448x448 |
| Batch Size | 16 | 16 | 16 |
| Optimizer | SGD | SGD | SGD |
| Learning Rate | 0.0001 | 0.0005 | 0.0001 |
| Weight Decay | 0.0005 | 0.0005 | 0.0005 |

ES[a] Early Stopping

*4.1.2 Datasets.* The implemented models were tested with two different datasets: CIFAR-10 [12] and the chicken carcass image dataset [1]. The CIFAR-10 dataset is used to verify the validity of the implemented models. By replicating the results from prior research with a benchmark dataset that includes a relatively high ratio of anomalies, we could first secure the reliability and validity of the implemented models before we test the models against the real-world data with an extremely low number of anomalies. To utilize the CIFAR-10 dataset in the context of one-class-classification-based anomaly detection, two classes (airplane and automobile) were used, and the ratio of airplane and automobile was set to 2:1, utilizing 7500 images (5,000:2,500) for model training.

The raw chicken carcass dataset was constructed as part of the secondary data construction project for AI training, administered by National Information Society Agency (NIA) in South Korea [1]. The chicken carcass image was collected by the company specialized in providing automated livestock management solution. All the collected carcass images were collected from the chicken meat processing factory and defects were distinguished by the livestock experts of the processing factory and the data collector. The defection cases were distinguished based on the characteristics related to product grading such as broken leg, injured skin, and bent wing. The total number of normal data is 30,493 and that of anomaly data is 85, which makes the ratio of 1:0.0028. This number of anomaly data is extremely small. Therefore, we selected 55 anomaly data and oversampled them to have 1,100 cases during the model training. Figure 2 illustrates the sample images of normal and abnormal (anomaly) in chicken carcass dataset and Table 2 describes the data composition used for training and testing of the models.

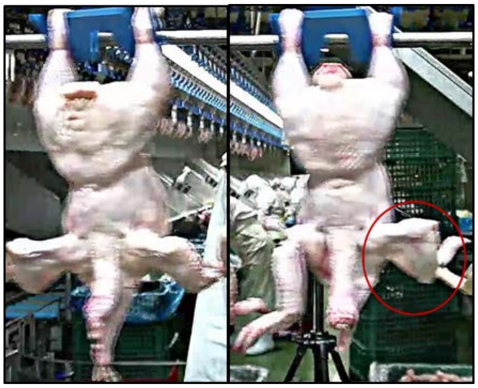

**Figure 2: Chicken Image example. Left: normal data; Right: anomaly data (wing torn apart with bruise).**

**Table 2: Dataset composition in CIFAR-10 and Chicken**

| Dataset | Purpose | Normal | Anomaly |
|---|---|---|---|
| CIFAR-10 | Train | 5,000 | 2,500 |
| | Test | 1,000 | 500 |
| Chicken Carcass dataset | Train | 30,223 | 1,100(55) |
| | Test | 270 | 30 |

## 4.2 Experiment Results

*4.2.1 Comparison Results.* To assess the performances of our model and the comparison models, AUROC (Area Under the Receiver Operating Characteristic curve) was measured for evaluation. Table 3 denotes the performance of each model on two different datasets. Among the compared models that were trained and tested with CIFAR-10, which represents the dataset with a relatively high proportion of anomaly, DeepSAD outperformed the other models, with 0.9966 AUROC. However, our proposed model also showed a relatively high AUROC score (0.9692) so we could assume the proposed model is effective in detecting the defects in the imbalanced dataset. The DevNet showed the lowest AUROC score but it was above 0.80 and the performance level was not significantly deviated from the outcome of the original study.

The comparisons made with the chicken carcass image dataset, which includes a significantly low proportion of abnormal cases, showed a different result than the prior comparison with CIFAR-10. As shown in Table 3, our proposed model showed the highest AUROC score of 0.9496, which is similar to the performance on CIFAR-10. However, the performance level deteriorated significantly with DevNet and DeepSAD. Especially in the case of DeepSAD, the AUROC marked only 0.5 in that it predicted all instances as normal. This shows that the difference between normal and anomaly data cannot be well distinguished by the traditional one-class classification model in an extremely imbalanced situation. On the other hand, the DevNet, though the score was dropped, it marked an AUROC of 0.7570. This result is consistent with the result of prior studies which support the effectiveness of an end-to-end one-class classification model in anomaly detection with an extremely imbalanced dataset. Our proposed model utilizes the loss inversion technique and FGSM attacks on adversarial learning in the end-to-end one-class classification model so as to secure the robustness of the model and produce the superior performance.

**Table 3: Model performance comparison**

| Dataset | CIFAR-10 | Chicken |
|---|---|---|
| DevNet | 0.8398 | 0.7570 |
| DeepSAD | **0.9966** | 0.500 |
| Ours | 0.9692 | **0.9496** |

As in Figure 3, The AUROC value is calculated for each model on each epoch during 10 epochs of training with DevNet, DeepSAD, and our model. With CIFAR-10, DeepSAD outperforms the other models during the whole 10 epochs. On the other hand, our model performs the best when evaluated on the chicken carcass dataset. It is also shown that DevNet is not stable in the beginning but gradually recover the performance on the chicken carcass dataset. Meanwhile, DeepSAD resulted in a constant AUROC value of 0.5 which implies that it was not possible to train the model in such a distribution condition.

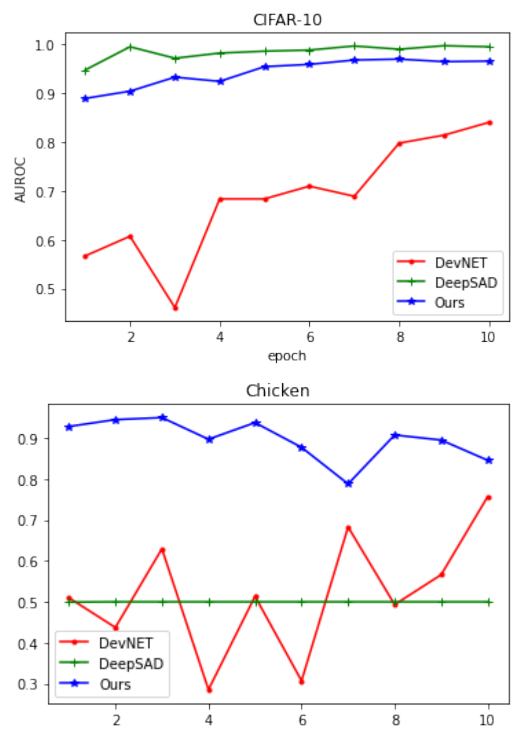


**Figure 3: AUROC changes during 10 epochs**

*4.2.2 Ablation Study.* To separately assess the influence of loss inversion and FGSM attack on our proposed model performance, we conducted an ablation study by setting up three experimental conditions: (1) baseline, in which either loss inversion or FGSM was not employed, (2) loss inversion (LI), in which the loss inversion technique was applied to anomaly cases as described in Section 3.4, and (3) loss inversion plus FGSM (LI+FGSM), in which the loss inversion technique was applied to anomaly cases and FGSM samples. As shown in Figure 4, compared to the baseline, the performance was noticeably better when the loss inversion technique was applied to anomaly cases. When the loss inversion technique was further applied to the data generated by FGSM, the model outperformed the two other models, indicating that the data generated by the FGSM attack can, to some extent, serve as unseen anomaly cases.

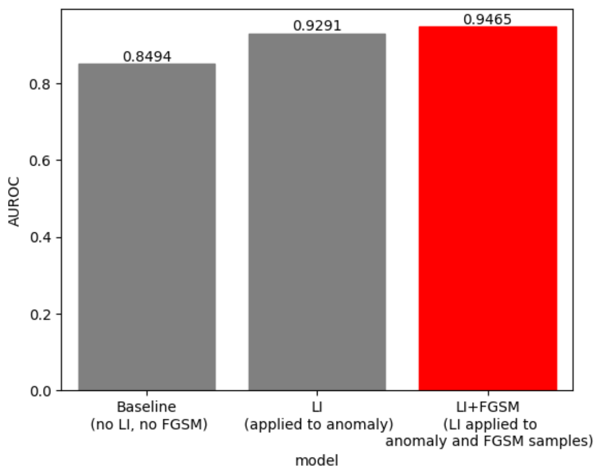


**Figure 4: Model comparisons with alternative combination of loss inversion and FGSM**

## 5 LIMITATION

The findings of this study need to be reevaluated using additional datasets, including various types of anomaly associated with different animals. The experiments in this research were conducted with CIFAR-10 and chicken carcass data due to the limited availability of livestock data. The robustness and generalization of the proposed model would be secured by testing the proposed model using additional datasets. Our ongoing research is to consider such issues. Currently, we are trying to apply the study findings to other animals including pigs and different types of data including video as video monitoring of livestock in the natural farming environment is becoming important for smart livestock farming.

## 6 CONCLUSION

This study proposed a deep learning-based anomaly (defect) detection method for an extremely imbalanced dataset, which is common in real-world meat processing. The performance comparison results using the CIFAR-10 dataset show that the proposed method is on par with DeepSAD and even outperform DevNet in performing simple classification. Further, experiment results show that the model outperform the existing models (i.e. DevNet and DeepSAD) for anomaly detection problems when validated on the chicken carcass dataset acquired from a livestock factory, with an extremely low proportion of defects. We expect the findings of this research would contribute to introducing visual defect detection in the livestock operations and resolving challenges in anomaly detection with one-class classification strategy from extremely imbalanced datasets. Moreover, this research is the first case that utilizes the FGSM attack and loss inversion together to detect anomalies. The experiment results support the effectiveness of integration of these two techniques, contributing to the AI research field regarding anomaly detection, covering both data-efficient learning and noise-resilient anomaly detection.

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