Validating Time Serial Images for Emotion Recognition

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Abstract

The pig emotion recognition (PER) reads the pig's emotions through the surveillance camera system. It can notify the husbandry workers if the system finds the pig's negative emotions. The PER is the idealistic system for pig husbandry workers, but practically applying the system is quite challenging without a suitable PER dataset. The pigs in the cage seldom move around the area, and the images captured are almost identical through the surveillance camera in the time series. The recurrent convolution neural networks may solve the problem. Still, with the single inputs to the architecture, the time serial images of the PER dataset produce misleading and biased experimental narration without a proper preprocessing method. To have adequate results from the time-serial imaging dataset, we propose the semi-shuffling approach to manage our PER dataset rather than what some researchers normally fully-shuffle the dataset without inspecting time-serial images. We have 98.45% validating accuracy as with fully-shuffling whole training and testing groups, but the validating accuracy reduces to 75.97% after applying the semi-shuffling training and testing dataset.

I. Introduction

Managing livestock is quite a challenging task as it increases pork consumption. Maintaining the highly standardized pigs' well-being is crucial for pork-producing companies to earn the trust of meat consumers. [1] Managing the pigs' well-being is highly sensitive and tiresome to husbandry workers since negligence work ethic could lead the meat company in peril. Besides, the husbandry workers in the livestock industries must tirelessly monitor livestock 24 hours and 7 days to ensure food safety from damaging meat quality. The demand of the autoamatation approaches is becoming common and shifting from the traditional ways to raise the pigs [2] [3]. Thus, the pig emotion recognition (PER) automatically could assist many workers free from boredom labor and improve the quality of pigs' well-being.

The PER reads the pig's emotions via an imaging device such as a surveillance camera. It notifies the monitoring husbandry workers if the pig shows constant negative emotion from the monitor screen. However, the reliable performance of the PER requires a suitable dataset to train and test. Besides, the pig's emotion-relevant dataset is rare and obtained mainly by partnership with agricultural research institutes. The most obtainable dataset is primitive states regarding the standard quality dataset since many agricultural research groups do not access even a simple refinery system. Training the obtained dataset may have 99% of accuracy instead of producing the reasonable validating accuracy. Many researchers mislead such a validating accuracy with the narrative explanation as a successful performance without inspecting the data samples and practical testing. Thus, we propose to semi-shuffle on the obtained PER dataset generally consisted of the video clips.

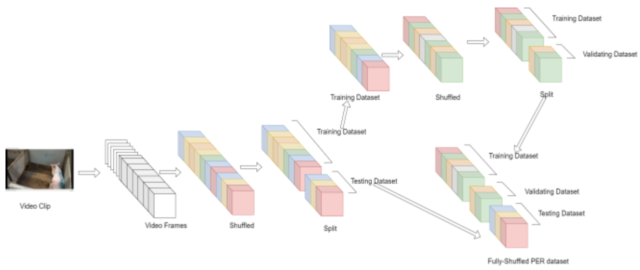

Fig. 1 The PER dataset is fully-shuffled in training and testing group.

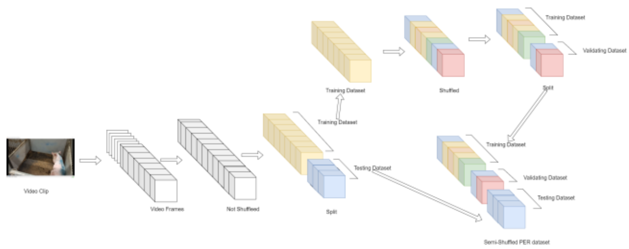

Fig. 2 The PER dataset is semi-shuffled in training and testing group.

II. The Semi-Shuffled PER Dataset

The PER dataset was created by the Department of Animal Science, Wageningen University and Research. The PER dataset consists of video clips and several captured images of pigs. Fig. 1 and Fig. 2 demonstrates how PER dataset is fully-shuffle and semi-shuffled.

From Fig. 1, many AI researchers typically train their model with a fully-shuffled dataset. The fully-shuffled dataset is to randomly mix data samples before separating them into training and testing. The fully-shuffling the PER dataset is suitable if the image samples show a dynamic appearance and are less likely identical to the neighboring data samples. However, fully-shuffling the PER dataset might not be appropriate since the pig generally does not move around for an extended period of time. As a pig stays in one location, the neighboring images generated from video clips are almost identical. Any neural network architecture with the kind of fully-shuffled PER dataset can have bias experimental results.

In contrast to the fully shuffled PER dataset, the semi-shuffled PER dataset from Fig. 2 is split into two groups of training and testing data before randomly mixing the data images. Isolating the testing dataset before randomly mixing the PER dataset is crucial for testing the pre-trained neural networks with the time serial images. After separating them into training and testing groups, we mix them randomly without affecting each other. Later, we split the training and validating dataset before training the Xception architecture. The testing dataset cannot be accessible until the model's training is completed.

III. Test Results

Our hardware computer consists of Intel ® Core ™ i5-10600K CPU @ 4.10GHz, 32 GB RAM, and GeForce RTX 2070. The Python V 3.8 application programming interface (API) has Tensorflow-GPU Versioned 2.2 with Keras's API. All images are resized to 224 × 224 pixels but is cropped to focus the pig segment by the end of preprocessing the PER dataset We split the training and testing dataset as a 70 to 30 ratio. The frame rate per second is 10 frames per second to generate the training samples. The number of epochs is 150 and the size of the mini-batch is 64. The learning rate is 10^{-3} and the activation function of the Xceptoin is the Rectified Linear Unit (ReLU).

Our PER dataset consists of video clips and images, and the total size of the PER dataset is 332GB. The PER dataset has 4 classifcations: isolation after feeding (IAF), isolation before feeding (IBF), paired after feeding (PAF), and paired before feeding (PBF).

As shown in Fig. 1 and Fig. 2, we trained the Xception algorithm with the PER dataset and generated the experimental results with the separated testing data from Table I. Our experimental results. From Table I, the Fully-shuffled PER dataset reached the 98% of the accuracy, recall, and F1-score, while the semi-shuffle significantly reduce down to 74%. The fully-shuffled PER dataset was previously mixed before splitting into the training and testing groups. The Xception architecture is already familiar with the testing dataset because the training and testing dataset is almost identical to each other. So, the accuracy of the fully-shuffled PER dataset is much higher than the semi-shuffled PER dataset.

On the other hand, the Xception architecture does not train with the image samples that is similar or identical to image samples from the testing dataset. In other words, the Xception architecture is not familiar with images from the testing dataset since they are completely different from the training dataset. Xception architecture tends to train the whole irrelevant features from background segments if images are not focused on the pig's segment. Therefore, we discovered that even a poorly managed dataset can reach more than 90% of accuracy and have a biased interpretation from it without considering the field test.

Table I. THE EXPERIMENTAL RESULTS OF THE PRE-TRAINED XCEPTION WITH THE TESTING DATASET.

PER Dataset	Accuracy	Recall	F1 Score
Fully-Shuffled	98.45 %	98.45 %	98.45 %
Semi-Shuffled	**75.97 %**	**75.97 %**	**74.21 %**

IV. Conclusion

In this paper, we proposed a semi-shuffling PER dataset if we have such time sequentially captured images. We discovered that even a poor managed dataset can have almost perfect accuracy as reaching 90%. Reasonably managed PER dataset can have poor performance, yet the performance can be improve if our aim is practically applicable to our farming system in the real life.

ACKNOWLEDGMENT

This research was supported by Basic Science Research Program through the Natoinal Research Foundatoin of Korea (NRF) funded by the Ministry of Education (2021R1A6A1A03043144).

References

[1] A. Kittawornrat and J. J. Zimmerman, "Toward a better understanding of pig behavior and pig welfare," Animal Health Research Reviews, vol. 12, pp. 25-32, 2011.

[2] S.-H. Oh and M. See, "Pork preference for consumers in China, Japan and South Korea," Asian-Australasian journal of animal sciences, vol. 25, p. 143, 2012.

[3] M. Sinclair, C. Fryer, and C. J. Phillips, "The benefits of improving animal welfare from the perspective of livestock stakeholders across Asia," Animals, vol. 9, p. 123, 2019.