ICIC Express Letters
Part B: Applications
Volume **15**, Number **2**, February **2024**
 ISSN 2185-2766
pp. **187–193**

CLASSIFYING PIG POSES FOR SMART PIGSTIES USING DEEP LEARNING

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Received June 2023; accepted August 2023

Abstract. *Pig postures play a crucial role in understanding the behavior and well-being of pigs in a pigsty environment. In this study, we propose a deep learning-based model for pig posture classification to alleviate the time-consuming and costly task of manual inspection. Our model leverages the power of deep learning techniques such as EfficientNet with convolution block attention module to automatically classify pig postures based on image data captured in the pigsty. Through rigorous experimentation, we have demonstrated the effectiveness of our model in accurately classifying various pig postures, achieving an accuracy of 94.73% and an F1 score of 0.91. Our proposed model has the potential to significantly streamline the process of monitoring pig postures in real time, allowing for more efficient and cost-effective management of pig farming operations. This study contributes to the field of animal behavior research by providing an innovative approach to understanding pig postures in a pigsty environment.*
Keywords: Computer vision, Convolutional neural network, Object detection, Convolution block attention module, Smart pigsty

1. **Introduction.** Recently, there has been a growing awareness of the need to improve animal welfare in the livestock environment, and active research has been conducted on animal behavior analysis according to the livestock environment and animal welfare [1]. Research shows that pigs reared in high welfare environments are more active and productive, while those reared in low welfare environments show abnormal behavior and reduced productivity [2,3]. Consumers are more likely to buy animal products produced in high welfare environments, even if they are more expensive, and improving animal welfare in livestock production is seen not only as a way to increase productivity, but also as a sustainable method [4,5]. In fact, many countries have introduced animal welfare certification schemes for housing environments that meet certain welfare standards and provide incentives for products produced in certified welfare environments [6].

Research into whether the livestock environment affects animal behavior has been ongoing and it has been found that the barn environment is associated with animal behavior. Therefore, understanding animal behavior is an important issue for researchers and practitioners as studies have shown a correlation between the barn environment and animal behavior. However, animal behavior is still manually observed by humans. Manually observing animal behavior is not only time consuming, but also remains a challenging task due to the difficulty of monitoring a large number of animals at the same time, compounded by their movements. Pigs are no exception. Early research into posture classification in pigs used sensor-based studies. However, using sensors alone has limitations in classifying different postures and the classification accuracy is low. This is because in reality there are different farming environments [7].

DOI: 10.24507/icicelb.15.02.187

In this study, pig postures are classified based on deep learning. The CNN (Convolutional Neural Networks) model was constructed by applying CBAM (Convolution Block Attention Module) to EfficientNet (B4), and pig images were obtained from AI Hub. Individual pig images were extracted from the acquired images using YOLO (You Only Look Once) and used to construct the dataset. The collected data did not have labelled postures, so the researchers manually labelled them. The training data was pre-processed using image enhancement and cutout, and the model was trained. The model achieved an accuracy of 94.73% and an F1 score of 0.91. The results were visually confirmed using Grad-CAM.

Through the proposed deep learning based pig posture classification model, it is possible to simultaneously check and classify the postures of a large number of pigs in a pig house. This is expected to aid future research into how pig welfare is affected by pig behavior and to assist pig farm managers.

The structure of this paper is as follows. In Section 2, we describe previous research on pig pose classification, including studies referenced in this work and those conducted before our study. Section 3 provides a detailed description of the overall process and experimental results of our study. In Section 4, we visually confirm and explain the results obtained through Grad-CAM and describe the expected effects of our study. Finally, Section 5 summarizes our study and discusses its limitations.

2. **Related Work.** In this section, we conducted a literature review of existing studies on CNN-based image classification and pig posture classification. Specifically, we examined several existing studies that used the CNN model for these tasks. Tan and Le proposed EfficientNet, which balances the depth, width, and resolution of the model through scaling to improve its performance [8]. Woo et al. proposed the CBAM, which consists of a channel attention module and a spatial attention module. This approach improves model performance without significantly increasing computational complexity [9]. YOLO is an object detection algorithm proposed in 2016, and various improved versions with enhanced performance have been proposed. Wang et al. proposed YOLOv7, which applies bag-of-freebies to achieving better performance than previous versions [10]. YOLO offers the advantage of faster speed compared to another object detection algorithm, R-CNN. DeVries and Taylor proposed cutout, a regularization technique that improves the performance of deep learning models by masking out random sections of training images [11]. Previously, it was impossible to explain the results of CNN-based models, but with Grad-CAM proposed by Selvaraju et al., it has become possible to visually explain the results of CNN-based models [12].

Shao et al. utilized semantic segmentation techniques to classify pig postures and compared the accuracy of different models. They found that ResNet had the highest accuracy of 92.26% [13]. However, in the study by Shao et al., EfficientNet was not included, whereas in this study, we utilize EfficientNet for pig posture classification. Yang et al. constructed a dataset of pig joint key-point data and compared the performance of models utilizing CBAM and models utilizing Triplet to recognize the size of pig bodies. This comparison is significant in exploring the application of various modules in CNN [14]. Witte and Gómez employed EfficientNet-B0 with YOLOv5 to classify postures in real time into two classes: 'Lying' and 'Not lying' [15]. The study classifies postures into four categories, indicating a greater diversity in posture classification compared to the two-class classification approach.

3. **Framework of the Proposed Method.** In this section, the overall framework for classifying pig postures for smart pigsties is presented. Figure 1 illustrates the comprehensive framework of the proposed system.

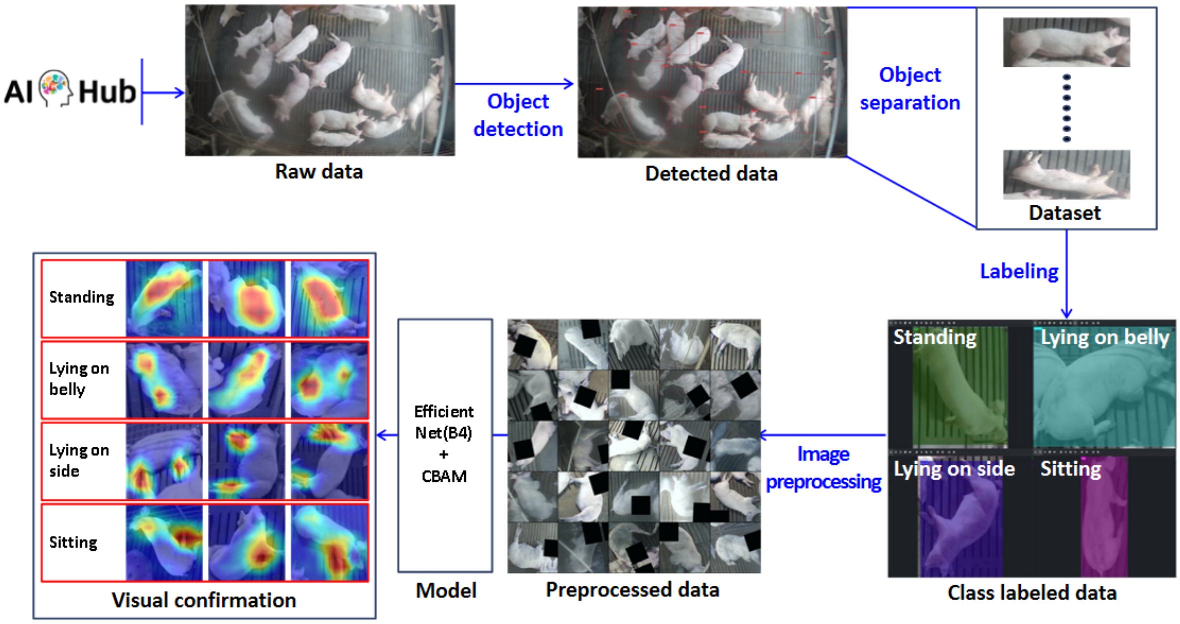

Figure 1. Overall system framework

3.1. **Dataset.** The pig image data used in this study was obtained from the open data platform AI Hub and organized. The dataset collected contained images of partially obscured or blurred pigs. We conducted object detection on the raw data to obtain image data containing a single pig's posture and constructed a dataset of images of individual pigs. In this study, YOLOv7 was chosen as the object recognition tool. However, the standard models provided by YOLOv7 did not include the posture of pigs, so it was necessary to train a model specifically for this study. Training the model required labelled coordinate values of the objects in the images, which were obtained by the researchers manually labelling the postures of the pigs. When YOLOv7 was trained using the acquired coordinate values, it showed excellent performance. Figure 2 shows the result of detecting pigs from the raw data through object detection.

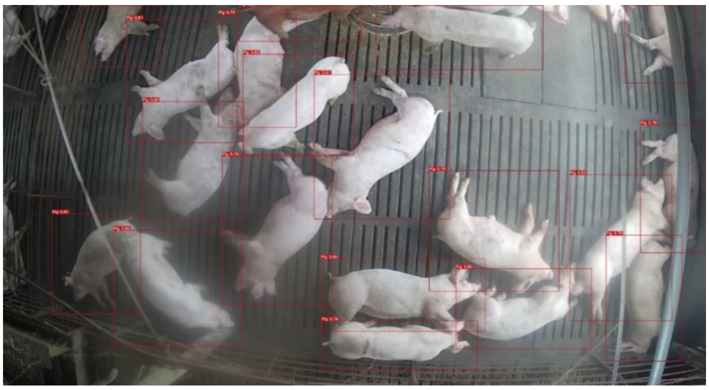

Figure 2. Pig images after object detection

Pigs for which the posture could not be accurately identified in the object detection results were removed from the dataset. This process resulted in a dataset of individual pig images for further analysis. The dataset used in this study did not provide class labels for the pig postures, so the pig posture classes were manually labelled as '*Standing*', '*Lying on belly*', '*Lying on side*' and '*Sitting*'. Although the labelling was based on common criteria, the subjective judgement of the researchers was partially reflected in cases where

Table 1. Number of data per class

	Train	Test
Standing	462	115
Lying on belly	1,752	437
Lying on side	3,369	842
Sitting	502	125
Total	6,085	1,519

the posture of the pig was not clear in the image. The total number of classified data is 7,604, which was divided in an 8 : 2 ratio for training (6,085) and testing (1,519). Table 1 shows the number of data for each class used in the study.

After labelling the data, we observed an imbalance in the number of data for each class, which can be attributed to the characteristics of the pig. According to a previous study, pigs spend more than 80% of their time lying down [16]. As a result, we were able to obtain more data for the '*Lying on belly*' and '*Lying on side*' classes and less data for the '*Standing*' and '*Sitting*' classes.

3.2. **Image preprocessing.** The two main problems have been addressed through data augmentation and cutout. The first problem is the issue of class imbalance, where there is an imbalance in the distribution of data across different classes. Deep learning models need to learn different types and patterns of images, but there was concern that the low number of standing and sitting data per class would prevent learning different types and patterns of images. To address overfitting that can occur with a small dataset, a common approach is to utilize image augmentation and transformation [17,18]. In this study, we employed Albumentation, a technique that has demonstrated excellent performance in computer vision image tasks, to apply image transformations before each training iteration. We generated diverse images by applying horizontal flipping, vertical flipping, rotation, and translation to the images with a 50% probability each.

The second problem is poor picture quality. It has been observed that images with partially occluded pigs or poor image quality can lead to a decrease in model performance. To address these issues, we aimed to improve model performance by applying cutout, which masks some parts of the training images, to a portion of the training image data. Specifically, we applied cutout to 70% of the total images before each training epoch.

3.3. **Modelling.** The model was built by applying CBAM to EfficientNet (B4), which is mainly used for image classification. CBAM can be applied to any CNN model and can effectively improve the performance of the model. In this study, EfficientNet (B4) + CBAM was modelled. The hyperparameters of the model are as follows: the optimizer is Adam, the loss function is cross-entropy, the max epoch is 80, the batch size is 32, and the learning rate is set at 0.0001.

4. Research Results.

4.1. **Classification results.** Training was performed based on the defined model. Table 2 shows the classification results of this study, showing the accuracy for each class.

Looking at the prediction results by class, the accuracy of '*Lying on side*' was relatively high, while the accuracy of '*Sitting*' was relatively low. '*Lying on side*' had a larger number of images in the dataset compared to other classes, which allowed the model to learn different patterns and angles of images. In addition, pigs lying on their sides have a distinct characteristic of legs outstretched to the side, which led to a high probability of correct classification. On the contrary, '*Sitting*' was unable to learn various patterns and angles of images due to the lack of data, and it was found to be misclassified as '*Standing*' or '*Lying on belly*' due to the similarity of Sitting's appearance to them. Here,

TABLE 2. Classification results

	Correct	Wrong	Accuracy
Standing	110	5	95.65%
Lying on belly	397	40	90.84%
Lying on side	831	11	98.69%
Sitting	101	24	80.80%
Total	1,439	80	94.73%

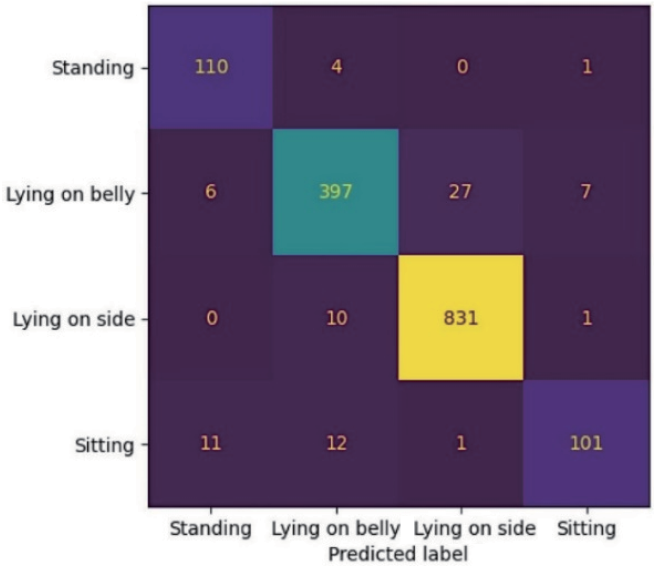

FIGURE 3. Confusion matrix of the classification results

the term "similarity of appearance" refers to the fact that the image of a sitting pig viewed from above can sometimes appear as if it is '*Standing*' or '*Lying on belly*' depending on the angle. The accuracy of '*Lying on belly*' was also relatively low, as pigs with their legs not fully bent were misclassified as Lying on side. Furthermore, the probability of misclassification increased relatively when there were multiple pigs in the image. It was observed that the model mostly classified the posture of pigs in the center of the image, but there were cases where it did not. Figure 3 shows the results of this study in a confusion matrix.

The performance of the model was evaluated using F1 score, as there was class imbalance in the data. F1 score uses the harmonic mean of Precision and Recall in the confusion matrix. Therefore, if one of precision or recall is relatively low, the value of F1 score also decreases. As a result, due to the relatively low accuracy of '*Lying on belly*' and '*Sitting*', the model recorded an F1 score of 0.91.

4.2. **Discussions.** In this section, we will present the results of Grad-CAM and describe the expected outcomes of this study. Figure 4 shows the classification results of the EfficientNet (B4) + CBAM model used in this study visually using Grad-CAM.

The results of Grad-CAM enabled us to visually confirm which parts of the image the deep learning model was attending to in order to classify the classes in this study. The model paid attention to the torso for '*Standing*', both the torso and legs for lying on belly, both legs for lying on side, and one leg or irregularly for '*Sitting*'. '*Standing*' was relatively often misclassified as Sitting. This is because there were many cases where the pig's posture appeared to be sitting depending on the angle of the image. We confirmed that there was a high rate of misclassification of the lying on belly position as lying on side, and similarly, lying on side was also frequently misclassified as lying on belly. This

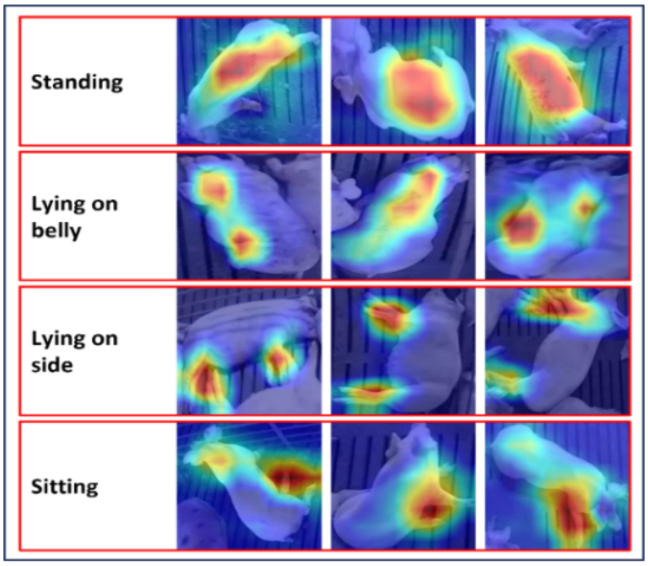

FIGURE 4. Grad-CAM results

phenomenon occurred when capturing images of pigs lying down on their back while stretching out one or both legs from a dorsal viewpoint. In the case of '*Sitting*', there was a relatively high rate of misclassification as lying on belly, which occurred when capturing images of pigs in a fully seated position from a dorsal viewpoint. This finding highlights the need to capture images of pigs from various angles to accurately classify their postures.

The association between the swine environment and pig behavior has been revealed, and research on pig posture classification is also continuously conducted. However, due to technical limitations and various reasons, research is mainly conducted on small pig groups rather than large-scale pig populations. By utilizing the pig posture classification model proposed in this study, it is possible to classify the postures of pigs in large-scale pig herds simultaneously. This allows for more meaningful research results to be obtained in environments that are closer to real-world pig farming conditions than previous studies. The findings from such research are expected to have practical implications for the actual pig farming industry, and ultimately contribute to the adoption and utilization of smart livestock facilities.

5. **Conclusions.** In this study, deep learning was utilized to classify pig postures for the purpose of understanding pig behavior in a pigsty. We utilized YOLO to detect the posture of pigs and obtain corresponding images. The acquired images were labeled by the researchers to construct the dataset. To train the model with various patterns of images, we preprocessed the data by applying image augmentation and cutout techniques. The model was built using EfficientNet (B4) with CBAM applied. The accuracy of the pig posture classification of this model was 94.73%, and the accuracy of lying on belly and sitting classes was lower than standing and lying on side classes. Due to the difference in accuracy between classes, the F1 score was 0.91. Then, the researchers used Grad-CAM to visually confirm the features of images for each class.

One of the limitations of this study is the imbalance in the number of data per class, particularly the relative scarcity of data in the standing and sitting classes due to the characteristics of pigs. Obtaining more diverse data of pigs could improve the model's accuracy through better learning. Another limitation is that the researcher's subjectivity was involved in classifying the pig's posture during the labeling process. This was necessary because the pig images obtained from the open data platform were not classified into four classes. If a more objective and professionally labeled dataset can be constructed, it would be possible to classify more detailed and diverse poses. Improving the classification accuracy of sitting, which is a posture that is generally difficult to classify and has limited data, is a challenge that must be addressed in pig posture classification.

Acknowledgment. This work is supported by Korea Institute for Advancement of Technology (KIAT) grant funded by the Korea Government (MOTIE) (P0017123, The Competency Development Program for Industry Specialist).

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