Automatic Posture Detection of pigs on real-time using YOLO framework

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***Abstract*: Recent research shows great importance in monitoring the behavior of livestock through posture, mainly to identify the health issues of livestock. Concerns about the health conditions of pigs are surging among the farmers for various reasons, for timely detection and treatment to control the disease and promote production. Unlike existing methods, posture detection can be accomplished by machine learning methods without human intervention at high accuracy. In this paper, our study mainly focuses on the posture detection of pigs using YOLO darkflow based machine learning technique. The YOLO algorithm gives higher real-time performance, with less computational resources. The proposed method detects and monitors the different posture of the pig, such as sitting, standing and lying posture on real time. The datasets used for training were labelled through manual process, which was obtained from nine pens at different timeline of long recorded video. The result shows that YOLO model was able to detect the posture with a mean average precision of 95.9%.**

***Index Terms*: Image Classification, Animal behavior, YOLO, Posture Detection**

I. INTRODUCTION

Deep learning technique has been integrated and incorporated in numerous technologies using the most decisive analysis result, extending from human's day-to-day life necessities to high-end machinery. Evidently, computer vision techniques have extended its usage in livestock monitoring processes, which plays an important role in the assessment of various animal behaviors. It also provides benefits by monitoring the livestock, due to the wide range of area leading to high cost [1]. With the advancement of technologies with the combination of machine learning techniques, the livestock industries have reaped great benefits [2-3]. There are many supportive researches, which indicates the health and welfare of the livestock are related to the livestock behaviors, that includes feeding [4], posture [5] and locomotive behavior [6]. In sow systems, researchers focus on 3D imaging to identify the standing and lying pigs, to identify the lactating behavior of the pig. The depth sensors were also used to identify the posture of the pig such as lying and lactation behavior [7] Kim et al. [8] also use a similar technique to recognize the lying and standing behaviors using the 3D images. Firstly, the noise from sensor images was removed by applying the interpolation technique, later the background subtraction method was used to detect standing and lying pigs. Some studies include the localization of the pigs in case of the aggressive events between the pigs [9]. Nasirahmadi et al [10] explain the posture detection using deep learning. He also compares different Convolutional neural network methods and found the R-FCN ResNet101 gives a high mean Average Precision (mAP) of 93%. Other than 3D images, 2D images also have been used for identifying the locomotion and posture detection, which focused on pixel movement [11] or features of the animals [12]. There are also study which focus on the fine-tuning the image noises for the clarity of captured images [13]. Despite these issues, machine learning technique like GAN, ResNet and VGG methods has increased the feasibility of image identification [14-16].

Among the object detection methods, YOLO [17] is considered as one of the fastest and less time-consuming methods. Many applications use the YOLO model such as traffic situation detecting pedestrian [18] and vehicles [19], livestock monitoring [20], aerial analysis [21] and even assist the impaired people to recognize the faces [22]. Seo at al [23] and Lee et al [24] applied the YOLO method to segment the toughing pigs and overlapping pig images respectively. Stephen et al [25] explain the importance of the behavior changes that are related to the disease and demonstrates the early detection and prevention of related diseases. Mathews et al [26] also proved that the early disease detection of pig by analysing the feeding behavior. Tail biting is also found by observing the lying posture of the pigs [27]. Scipioni et al [28] clarify that dog-sitting position of the pig as the stereotypes with abnormal behavior of the pig, indication of lack in stimuli. Dog-sitting posture in pigs can be considered one of the issues which leads to the serious spinal nerve issue [29] and in some cases, it also indicates the salt intoxication [30]. The study of disease prevention mainly focuses on locomotive and feeding behavior and there are very little researches that focus on posture detection to identify or prevent the disease.

In addition to this, the issue of monitoring the livestock in real-time, especially in large scale barns, are not feasible [31]. And it is also impossible to manually monitor the individual pigs by either farmer or researcher. Hence exploiting state-of-the-art technologies like machine learning, pigs can be monitored from different pens in a cost-effective way. Hence, we use the deep learning-based YOLO model to detect the posture of the pigs, to monitor the behavior of the pig. The behavior monitoring, along with machine learning technique could help in early detection of health issues.

II. Data and Methods

Data Collection

In the image acquisition part, the dataset is obtained from three cameras, which monitors nine different pens. The images used in the study where recorded from titled top angle camera. The angle was set to capture the sitting posture of the pig, which might be different to capture through the top-view. With obtained video files from the camera, the process is easier compared to obtaining the image files. The continuous images can be used for detailed analysis. To avoid a large memory cost of the images, the pixels of 720*480 was used for training and detecting the posture of the pig. During the recording process, the light was turned-on for clearer images.

Figure 1 : Example images used for training

The labels of pig are divided into six classes, under two categories such as Posture and Non-Posture. The Posture category consist of sitting_pig, lying_pig and standing_pig, to determine the behavior of pig. Due to the camera angle, few pigs were not completely visible in the images. Therefore, the three classes such as multi_pig, part_of_pig and other_pig were categorized under non-posture pigs. It also decreases the practical difficulty that raises uncertainty of unidentified pigs in the image. Fig 1 shows the example images used to train and build the model.

Overview of the model

In this study, the grown-up pigs are used for the detection process. First, the images are labelled manually, to generate the XML files, which contains the position coordinates and the label names. Due to the space constraint in the pig pen, the pigs are cramped together, which makes it difficult to differentiate two attached pigs through image analysis. Considering all the possibilities, the labels of the pig are divided into six categories such as "lying_pig", "sitting_pig", "standing_pig", "multi_pig", "part_of_pig" and "other_pig". The overall process of the posture detection is classified into the two processes, Training process and Posture Detection. Figure 2 represents an overview of our process.

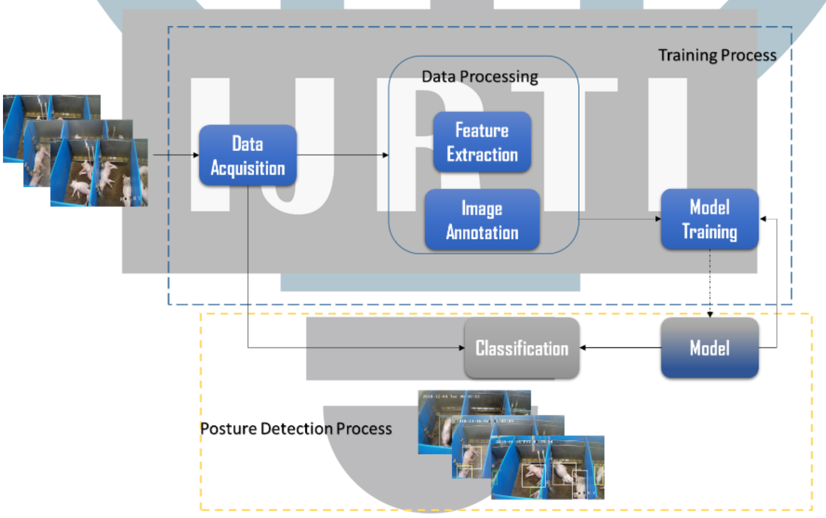

Figure 2. Overview of the posture detection model

Training Process.

In order to train the images for posture detection, the three steps are ensured namely data acquisition, data processing, and model training. Firstly, all the images are annotated using the Labellmg tool [32], manually by marking the bounding boxes to recognize the co-ordinates and labels. All the postures in each image are labelled in the annotated files and generated into XML files that are trained along with the respective images. The total number of each labeled postured is summarized in table 1.

Table 1. Dataset details for posture detection

Labels	Training Process [No of class images: 21409]	Testing Process[No of class images : 1792]
Sitting	3345	67
Standing	3384	1130
Lying	5590	2852
Multi	4030	510
Part-of	3432	3019
Other	1628	373

The images and annotation files are coupled to train the posture using the tiny YOLO model. YOLO is an object detection technique that uses the CNN framework to accurate object detection with grid technique. In this study, tiny yolov3 is used, because it occupies less memory space and speeds up the detection. The main concept is to speed up the detection process using the tiny YOLO involves binding the localizer and classifier into a CNN architecture to produce an efficient result.

Posture detection of the pig is impractical through the manual process; hence the smart posture detection process is necessary to detection the posture or any behavioral changes on a real-time basis. And it is necessary to consider discriminating postures among the group for more efficient identification. Therefore, the model is created with the trained images to identify the posture detection that can be used in a smart surveillance system.

Posture Detection Module:

In the posture detection process, the images obtained from the camera are tested using the generated model using tiny yolo model. Both the images and videos can be used to detect the posture of the pigs. All the postures in the image are identified and marked with bounding boxes. Along with the result image, text and json files are created, that contains the bounding box co-ordinates, labels and confidence score. Both the files can be integrated in required applications.

Performance Evaluation method

The most credible evaluation method for the object detection technique is mean Average Precision (mAP). Intersection over Union (IoU) is the primitive method to find the intersection of two objects. In other words, IoU is the ratio of the area of the intersection and union of the predicted object and the ground truth object. Ground truth object refers to the original bounding box which was used in the training dataset.

The IoU can be represented as in equation (1):

$$IoU = \frac{Area\ of\ intersection}{Area\ of\ Union} \qquad (1)$$

IoU is calculated to determine whether the prediction box is true positive, true negative false positive or false negative. This can be found using the threshold values as shown in table 2.

Table 2. Table of IoU and precision values

IoU [Threshold]	Precision
>0.5	True Positive
<0.5	False Positive
>0.5 [Object missing]	False Negative

Assuming that there will be some intersection with the bounding boxes, the true negation is omitted in the calculation. Similarly, the Precision and recall curve can be identified using the IoU. With the area of the curve, the Average Precision is calculated as shown in the equation (2)

$$AP = \int_0^1 p(r)dr \qquad (2)$$

Where, Precision/recall (p(r)) falls between 0 and 1. Then, mAP is calculated by calculating the mean of AP as stated in equation (3)

$$mAP = \frac{1}{Q}\sum_{q=1}^{Q} AP(q) \qquad (3)$$

Where Q is the number of objects in the evaluation process.

Figure 3: Result of posture detected images from three different camera

III. EXPERIMENTAL RESULTS

In this study, tiny yolo with CNN based technique is used to detect the posture, to monitor the behavior of the pigs. From the total dataset, the 21409 images were used as the training set and the 1792 images were used for the testing set. For annotating the ground-truth (training) images, the labellmg tool was used. The training was performed with the environment of Ubuntu 18.04 using a Nvidia Titan X GPU in the conda virtual environment. In order to collect the required amount of dog-sitting posture images, we installed three cameras around the pig pens which recorded the video and later converted to images with the interval 5 seconds. The resolution image frame comprises to HD, and the frame rate comprises 5 fps (frame per second).

The proposed models (tiny YOLO) were trained and tested on the dataset that consists of 16 video files in which each files contains multiple images with the following six different classes: lying_pig", "sitting_pig", "standing_pig", "multi_pig", "part_of_pig" and "other_pig". In the experiment, the only three classes are identified as main postures, and the performance of the behavior detection can be detected while using the proposed method. Due to the lack of open sources related to the pig, we used the custom train pig images with the deep learning libraries such as YOLO darkflow that consist of CNN architecture to train the images. The images were trained with the learning rate of 0.001 with 100 epochs and it took three days to train and create the model.

Posture detection results

During the testing process, images that are not used for training, were used to evaluate the accuracy of the posture detection model. The test data set contained images from the same pen which were selected from different time frame that included the different activities like feeding, resting and locomotion.

Fig 3 shows the result of the test images with the bounding boxes which shows posture detection of all six classes. Most posture of the pigs are detected and identified. The accurate result was obtained by constant learning and training process.

The Fig 4 shows some of the issues faced, which are explained as follows,

1. In test result, we faced some exceptions like Fig 4a and Fig 4b. In Fig 4b, the model failed to recognize the "sitting_pig" and mistook the posture for the "other_pig".
2. Few images are not identified as seen in Fig 4a.

In addition to these failed cases, there are also cases where the detection results are very accurate. When the two or three pigs are together, it makes it difficult to identify the posture of the pig. But, under the meticulous labeling and training, the yolo model performs exceptionally by differentiating the postures such as "sitting_pig", "part_of_pig" and "multi_pig" as shown in Fig 4c.

(a)

(b)

(c)

Figure 4: Result of posture detected images with special cases: (a) Failed Detection scenario (b) Improper Detection

of sitting pig scenario (c) Detection of posture in multi pig scenario

Performance Analysis:

A total of 1792 class images were used for the evaluation process, which compromises of six different classes of pigs as shown in Fig 5. Due to the angle of the camera is little tilted to recognize the sitting pigs, most of the pigs are hidden behind the bars. Therefore, the test images contain a large number of "part_of_pig" images Although the method shows good performance in posture detection, it may tend to fail in some cases. Therefore, the precision results can be manipulated to find the accuracy of the model. True positive, false positive, true negative and false negative are manipulated for calculating the intersection and union of the bounding boxes between the ground truth and tested.

The detected result for the images with the true positive and false positive is shown in Fig 6. In case of sitting pigs, the false positive is less than 10, achieving a high level of detection with less images for training. Hence, the proposed technique for posture detection in pigs with normal 2D cameras produced a high level of detection performance which results in 95.94% of mAP as shown in Fig 7.

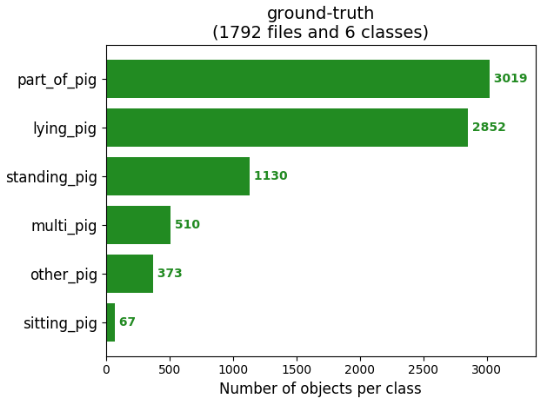

Figure 5: Ground truth of the test dataset

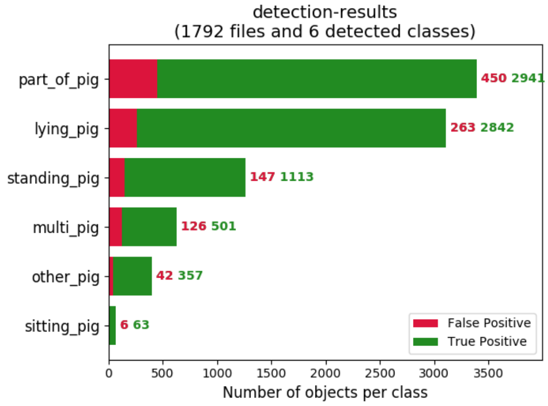

Figure 6: Detection result of the test dataset

In Fig 8, the log average miss rate for the sitting and others postures are less, due to the lack of images, which will be rectified with constant transfer learning to the model. By attaining high accuracy, it will be easier for the farmer to analysis the reason for the sitting posture and determine the behavior of the pig.

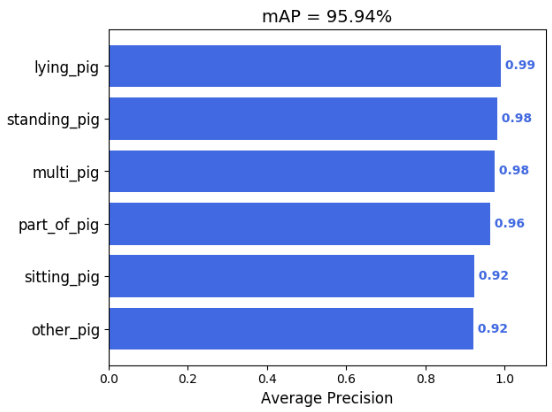

Figure 7: mAP result of the test dataset

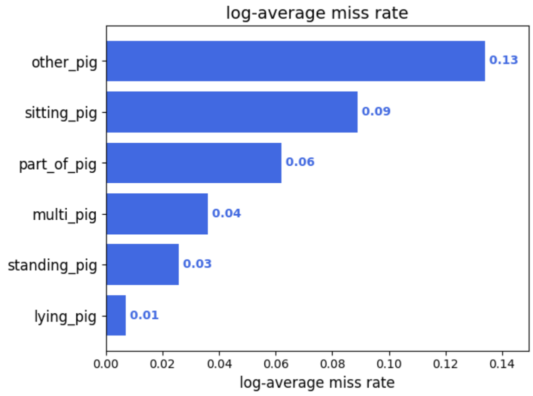

Figure 8: Log average miss rate plot for the test dataset

IV. DISCUSSION

In this study, we have attained a satisfactory result of posture detection, although there were few output cases of failed detection or incorrect detection. mismatch recognitions as shown in Fig 4b. In contrast, even when the floor or pig is dirty, the method can handle the situation and identify the pig as shown in Fig 4c. One of the important concerns of the experiment with a different range of posture is the overfitting problem. Therefore, the image trained for the model contains the same breed of pig, which almost resembles same in shape and size. Also, the images from different time frame were taken to overcome the imbalance number of labels for training.

Table 3. Comparison of performance result

Methods	**AP**			**mAP**
	Standing Pig	***Lying Pig***	***Sitting Pig***	
Faster R-CNN[10]	0.93	0.92	-	0.91
R-FCN [10]	0.93	0.95	-	0.93
SSD [10]	0.76	0.79	-	0.76
SVM [33]	-	0.94	-	0.94
YOLO	0.99	0.98	0.92	0.95

The accuracy of 95% is achieved through the YOLO model, compared the ResNet model which gives 93% accuracy for detecting the standing and lying pigs [10]. Support vector method provides high accuracy of 94% mAP, but the RGB images are converted to binary images for classification and prediction [33]. The table 3 shows the comparison of the posture detection with current and proposed model.

Although the pigs with the same breed are used for training, it will cause less accuracy when tested with other pens or piggery. The number of pigs allocated in each pen are limited to two or three, to reduce the touching of pigs in the image, otherwise, it will increase the difficulty of posture detection [25]. Still, the training is done with the careful handling of multiple pigs, which helps to differentiate the posture of pig individually. Identifying the behavior of pigs could identify early detection of disease. Dog-sitting pigs are the major concern in the production management which raises the suspicion of a few health issues such as salt intoxication or spinal nerve problems and some time it also indicates the virus infection in the piglets. If the pig is affected by salt intoxication and not identified in time, it may even cause sudden death. Also, posture is one of the indications of the issues in the spinal nerve. They might be difficult to stand or lay for a long time and sit mostly in the dog sitting posture. Therefore, by identifying the sitting posture through deep learning will help the farmer pay more attention to the pig and prevent from any major events. This study provides a reliable and feasible method for posture detection in pig to improve health issues by analyzing the posture of the pig in real time.

V. CONCLUSION

In this paper, a deep learning YOLO method is applied for the automatic identification of pig's six posture including sitting, lying, standing, multi, part-of and other pigs. The results of the testing process showed a high level of mAP with 95.94% and high processing speed for the different postures using the Yolo model. The proposed method shows average precision of 0.99, 0.98 and 0.92 for lying, standing and sitting pig respectively. The model performed well in monitoring the pigs, with a high degree of accuracy. In pig farms, monitoring the animal behavior is more important. The posture detection of the sitting pig, might help in identifying and preventing few diseases like salt intoxication and spinal nerve issues. With the flexible and robust development with the increase images and training, the model can refine and installed in other piggeries for the reliable posture detection.

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