Deep Learning-Based Piglet Crushing Detection on Edge Computing Platforms

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***Abstract*—In this study, we aim to demonstrate the effectiveness of integrating Artificial Intelligence of Things (AIoT) with deep learning to detect piglet crushing incidents by sows, a leading cause of piglet mortality on pig farms. We use a You Only Look Once (YOLO) based deep learning approach to detect piglet crushing events in the pig pen. Considering the limitations of edge AIoT computing platforms, which have limited computational power, the original YOLO model is optimized using TensorFlow Lite and TensorRT. We evaluate the performance of the lightweight YOLO-based piglet crush detection model on various single-board computers (SBCs), including the Jetson Nano, Raspberry Pi, and Jetson Orin Nano, to validate its real-world applicability and effectiveness. Initial performance evaluations focus on two key metrics: computation time per frame and cost efficiency. The results indicate that the Jetson Orin Nano achieves the lowest computation time, while the Jetson Nano provides the highest cost efficiency. We plan to extend the performance comparison to more resource-constrained IoT devices, such as those based on the ESP32.**

I. Introduction

In the pig industry, piglet suffocation due to crushing by sows significantly contributes to piglet mortality. Specifically, during the lactation period, suffocation accounts for 55% of all piglet deaths [1]. When a piglet crushing event occurs, the piglet can die within a few seconds, making rapid detection and an appropriate response crucial to reducing mortality and improving the profitability of pig farms.

Recently, Artificial Intelligence of Things (AIoT) technology, which integrates Artificial Intelligence (AI) with the Internet of Things (IoT), has gained attention as a potential solution to this problem, enabling faster and more accurate detection through the deep neural network (DNN)-based detection using images captured by IoT cameras [2]. Specifically, by implementing edge AI technology, where the DNN model is executed directly on edge IoT devices, communication delays can be minimized, thereby improving detection performance for the piglet crushing incidents. However, given the limited computational resources of IoT devices, it is necessary to develop a lightweight DNN model, so that it can be deployed on edge IoT devices, which may deteriorate the overall performance [3]. Additionally, in practice, it is important to evaluate the cost-effectiveness of the IoT system, as edge AI devices can be expensive.

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In this study, we implement an AIoT-based system for detecting piglet crushing incidents using the You Only Look Once (YOLO) model, which is one of the most popular DNN models for object detection [4]. To ensure that the model can operate on IoT devices with limited computational power, we lightweight the YOLO model using TensorFlow Lite [5] and TensorRT [6], making it suitable for execution on edge devices. We then deploy the DNN-based piglet crushing detection scheme on various single-board computers (SBCs) [7], including the Jetson Nano, Raspberry Pi, and Jetson Orin Nano, and compare their performance in terms of computation time and cost efficiency to evaluate real-world applicability. This evaluation demonstrates the suitability of our AIoT-based piglet crushing detection system for smart pig farming environments.

II. Data Preparation, Training, and Model Optimization

A. Data Pre-processing and Model Training

To develop the YOLO-based piglet crushing detection system, we used the lightweight YOLOv5s and YOLOv8s models due to their fast prediction speed and low computational complexity, making them suitable for IoT deployment. To train the YOLO models, we utilized video data obtained from free farrowing pens measuring 2.4 × 2.3 meters, with recordings taken 24 hours after the start of farrowing. The video data was collected from June to August 2022 on an 8,000-head commercial pig farm. The camera used to capture piglet crushing events was installed at a height of 1.5 meters and had a resolution of 1920 × 1080 at 30 frames per second (FPS).

After collecting the video data, segments containing crush events were extracted, separated into individual frames, and labeled using YOLO bounding boxes. To enhance the dataset, data augmentation techniques such as rotation and flipping were applied, resulting in a total of 9,792 images, which were then split into training and evaluation sets at a 7:3 ratio. Using this dataset, the YOLO models were trained to accurately detect piglet crushing events. YOLOv5s and YOLOv8s had accuracies of 0.998 and 0.997, respectively.

B. Development of Lightweight DNN Model

Although we used relatively small YOLO models, such as YOLOv5s and YOLOv8s, they can still pose computational challenges for typical IoT devices. Therefore, we further optimized the trained YOLO models using TensorFlow Lite and TensorRT. The optimized models for detecting piglet crushing events were deployed on four well-known SBCs for

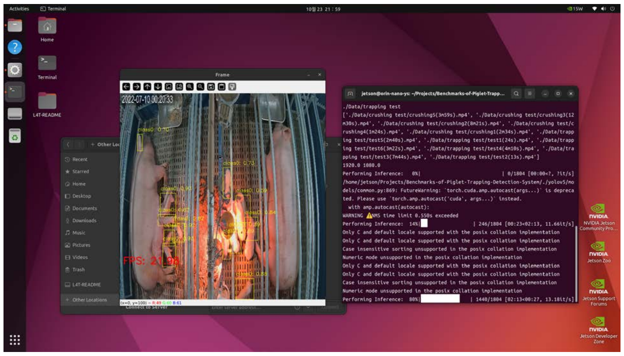

Fig. 1. Implementation Results of YOLO Models on Jetson Orin Nano.

IoT platforms: Raspberry Pi 4, Raspberry Pi 5, Jetson Orin Nano, and Jetson Nano. These devices were selected for their low power consumption, cost-effectiveness, and compact size. We note that during deployment, the Raspberry Pi boards utilized TensorFlow Lite weights, whereas the Jetson models used TensorRT weights for optimization. The Raspberry Pi models are affordable, but have memory and CPU limitations. the Jetson devices, with their powerful GPUs and TensorRT optimization, provided superior real-time object detection.

III. Performance Evaluation

In the performance evaluation, we first compared the computation time required to process one image, measured in milliseconds per frame (ms/frame), for different base YOLO models and SBCs, as shown in Table 1. It is important to note that computation time is critical to enable real-time operation of the piglet crushing detection scheme. In addition, shorter computation times allow the SBCs to perform other tasks, further improving the efficiency of the IoT platform for a smart pig farm.

As shown in the results, the Raspberry Pi 4 running YOLOv8s provides the worst performance, with a computation time of 3049.48 ms per frame, which is insufficient for real-time operation. In contrast, the Jetson Orin Nano running YOLOv5s achieves the best performance, with a computation time of 51.44 ms per frame, which is low enough for real-time operation. Additionally, the Jetson Nano also achieves a low processing time of 149.31 ms per frame, allowing for real-time operation.

TABLE I
Computation time per frame and cost efficiency for different SBC and YOLO models.

SBC	Weight	ms per frame	Cost efficiency
Raspberry Pi 4	YOLOv5s.tflite	2040.44	71415.44
Raspberry Pi 4	YOLOv8s.tflite	3049.48	106731.96
Raspberry Pi 5	YOLOv5s.tflite	683.89	54711.57
Raspberry Pi 5	YOLOv8s.tflite	992.01	79361.06
Jetson Nano	YOLOv5s.engine	149.31	22247.20
Jetson Nano	YOLOv8s.engine	201.56	30033.46
Jetson Orin Nano	YOLOv5s.engine	51.43	25666.88
Jetson Orin Nano	YOLOv8s.engine	52.36	26128.81

Next, we compared the performance of different SBCs in terms of cost effectiveness. Specifically, it is important to determine whether the AIoT system for a smart farm is affordable, given that many pig farms in South Korea are relatively small. To assess this, we defined cost effectiveness as the computation time multiplied by the price of the SBC, with a lower value indicating a more cost-effective system.

For the prices of the SBCs, we used the base prices as of October 2024, which are as follows: Raspberry Pi 4 at \$35, Raspberry Pi 5 at \$80, Jetson Nano at \$149, and Jetson Orin Nano at \$499. Table 1 shows the cost effectiveness for each SBC. From the results, we observe that the Jetson Nano with YOLOv5s has the best cost effectiveness, while the Raspberry Pi 4 has the worst ratio. Although the Raspberry Pi is significantly cheaper compared to the Jetson Nano and Jetson Orin Nano, its low cost does not compensate for its long computation time. From these results, we can infer that while high-end SBCs such as the Jetson Orin Nano offer superior performance, mid-range options such as the Jetson Nano offer a better balance between cost and efficiency, making them more suitable for practical deployment in AIoT-based smart farming systems.

IV. Conclusion and Future Work

We evaluated the suitability of a deep learning-based piglet crushing detection system for smart pig farms using various SBCs as AIoT platforms. Specifically, we developed a YOLO-based piglet crushing detection scheme that was optimized to fit into SBCs. During the performance evaluation, we compared two key performance metrics, namely, computation time per frame and cost efficiency, across three different SBCs: Raspberry Pi, Jetson Nano, and Jetson Orin Nano. Our results showed that the Jetson Orin Nano achieved the lowest computation time, while the Jetson Nano provided the best cost efficiency. Conversely, the Raspberry Pi, which lacks dedicated DNN capabilities, performed the worst in both metrics. In future work, we plan to extend the performance comparison to more resource-constrained IoT devices, such as ESP32-based devices, and develop more efficient DNN weight optimization algorithms customized for smart pig farming environments.

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