Computer vision on the edge: A computing framework for high-throughput phenotyping in livestock operations

T. Bresolin[1], R. Ferreira[2], G. J. M. Rosa[2] and J. R. R. Dórea[2,3,*]
[1]*Department of Animal Science, University of Illinois Urbana-Champaign, Urbana, IL 61801, USA*
[2]*Department of Animal and Dairy Sciences, University of Wisconsin, Madison, WI 53706, USA*
[3]*Department of Biological Systems Engineering, University of Wisconsin, Madison, WI 53706, USA*
[*]Corresponding author: João R. R. Dórea, joao.dorea@wisc.edu

Abstract

Computer vision systems (CVS) have gained attention in agriculture as a powerful technology for high-throughput phenotyping. However, implementing CVS in commercial farms can be challenging due to the massive amounts of data generated and the limitation of Internet bandwidth and latency when using on-premises or cloud computing. To address this challenge, we propose utilizing an edge computing system, which enables real-time monitoring and large-scale data collection by processing data locally at the edge devices. In this study, we developed a low-cost edge computing system designed primarily to video-image livestock animals in farm conditions. The system is based on 3D cameras (n = 29), known as edge devices, each connected to an edge node, here a single-board computer (Nvidia Jetson Nano). The edge nodes communicate through a local Wi-Fi network to an edge server, which also uses an Nvidia Jetson Nano that monitors and manages the edge nodes. The edge computing framework was programmed using the Bash command language interpreter. Log files are generated daily for monitoring the edge system, ensuring the smooth operation of the entire system. One of the key advantages of this system is that it allows for image recording in real-time (24/7) and can process data on the edge system, store it locally, or transfer it to a cloud system. Additionally, other sensing technologies, such as wearable and weather sensors, can be connected to the edge system, expanding the range of data that can be collected. This breakthrough in using high-throughput digital technologies to collect animal and environmental information has the potential to revolutionize how data is collected and processed on farms.

Keywords: camera system, data collection, edge-computing, image recording

Introduction

Livestock farms play a fundamental role in providing food to the global population and are a key source of livelihood (FAO, 2018; Rosa, 2021). The increasing demand for food and the growing global population has led to large-scale animal production systems. Such change in production systems scale has also led to new development and implementation of sensing technologies to improve animal monitoring and farm management decisions. (Berckmans, 2017; Rao et al., 2020, Rosa, 2021). The adoption of sensing technologies such as cameras, wearable sensors, and spectrometers in livestock farms is leading to the emerging concept of precision livestock farming (PLF), where high-frequency information is collected from animals and the environment, allowing the detection of valuable characteristics and events (Berckmans, 2017; Benjamin and Yik, 2019; Rosa, 2021). Therefore, these technologies in PLF are explored to optimize production, improve animal health and welfare, and mitigate the environmental footprint (Berckmans, 2017; Rosa, 2021). However, implementing these technologies in commercial farms faces challenges due to the massive amount of data produced, which often relies on continuous Internet access (O'Grady et al., 2019; Rosa, 2021). This is because precision technologies require significant bandwidth, latency, processing speed, and short response time that might be necessary, in addition to the data size that could heavily load the network (Shi et al., 2016). Many farmers, particularly in remote rural areas, have poor- or non-Internet access (O'Grady et al., 2019), which precludes the use of these technologies. One possible solution to these challenges is edge computing, which allows data to be processed at the farm level rather than transferred over the network (Shi et al., 2016). Edge computing might reduce costs associated with computing, storage, and network resources by deploying services at the edge, which reduces service response times and increases the quality of service and security of applications (Lin et al., 2017).

Edge computing has been successfully implemented and used for various agriculture applications (Fan and Gao, 2018; Zamora-Izquierdo et al., 2019; Zhang et al., 2020; Akhtar et al., 2021; Guillén et al., 2021; Premkumar and Sigappi, 2022) and has promising potential for livestock farming, with some applications in poultry (Yang et al., 2019; Debauche et al., 2020a) and cattle (Bhargava et al., 2016; Caria et al., 2017; Alonso et al., 2020; Debauche et al., 2020b). This study presents our initial work on developing an edge computing system for a computer vision application. The system is designed to collect and process information at the farm level. We aim to demonstrate its potential to enable reliable, precise, and efficient animal monitoring systems that will help farmers make informed decisions in their day-to-day work. This could potentially overcome data transfer limitations over the network and accelerate the adoption of novel precision technologies in commercial farms.

Materials and methods

Animals and farm description

The edge computing system for computer vision application was developed at the University of Wisconsin-Madison and deployed at the Marshfield Agricultural Research Station (Marshfield-WI). Twenty-nine individual pens with dimensions 5 m × 9 m, representing 45 square meters, each with an individual water tank and feed trough, were used. Heifers were fed twice daily with a standard farm diet according to age, whereas water was offered ad-libitum. Light and temperature changed with the natural environmental condition where the farm is located. Each pen allows grouping up to eight heifers managed together from weaning (~2-month-old) to first conception (~15-month-old). During the experiment, 200 heifers were monitored using this edge computing framework. An overview of the edge computing system is depicted in Figure 1, and the system architecture is further described in the next section.

Figure 1: Overview of the edge computing system developed and deployed for video-imaging dairy heifers. From right to left are the Nvidia Jetson Nano, placed inside a waterproof and dustproof box, and the 3D camera.

System architecture

This section presents the edge computing system architecture developed for video-imaging animals in farm conditions. The edge computing system comprises three essential parts: edge devices, nodes, and servers (Figure 2). The edge devices are 3D cameras (Intel® RealSense™ Depth Camera D455) connected to the edge node through USB-C to USB cable. The 3D cameras were placed above the water trough, one per pen (n =

29), at 3 m height (top-down view), allowing video-recording animals when drinking. The edge nodes are based on Nvidia Jetson Nano single-board computers equipped with 128-core CUDA Maxwell GPU, Quad-core ARM A57@1.43GHz CPU, and 4GB 64-bit LPDDR4@25.6 GB/s memory. A microSD card with a capacity of 250GB was used to install the operating system (Linux4Tegra) and to serve as data storage. Linix4Tegra (L4T) is the NVIDIA® Jetson™ Linux Driver Package that supports the package for Nvidia Jetson, including Linux Kernel 4.9, bootloader, NVIDIA drivers, flashing utilities, and sample filesystem based on Ubuntu 18.04 (see https://developer.nvidia.com/embedded/develop/software for more details). In addition, a Wireless-AC8265 Dual Mode Intel AC8265 Wireless NIC Module, which supports dual-band (2.4GHz/5GHz) Wi-Fi, was incorporated into the Nvidia Jetson Nano. This type of single-board computer offers a less complex setting when compared to a traditional desktop computer, a more affordable solution for such implementation, and low power consumption (5 Watts). Once Nvidia Jetson Nano is equipped with the GPU, it allows for performing high-frequency inference by deploying machine learning algorithms if needed.

The edge node and server are an integral part of the system, and they share information locally over the network through a communication protocol 802.11 Wi-Fi. The edge server, a computer capable of running Linux, is connected to a local storage system with a capacity of 8TB. This allows for data transferred from nodes to be stored locally, which can have its ability easily expanded if necessary. Future implementations can use this framework and send the data to a cloud system if the Internet is not limited. The edge server manages and controls the edge nodes by assigning tasks related to the devices or directly to the edge nodes, such as starting and stopping video-imaging, running system updates or any upgrade needed for the edge devices, and data transfer protocol. The edge-computing framework was programmed using the Bash command language interpreter.

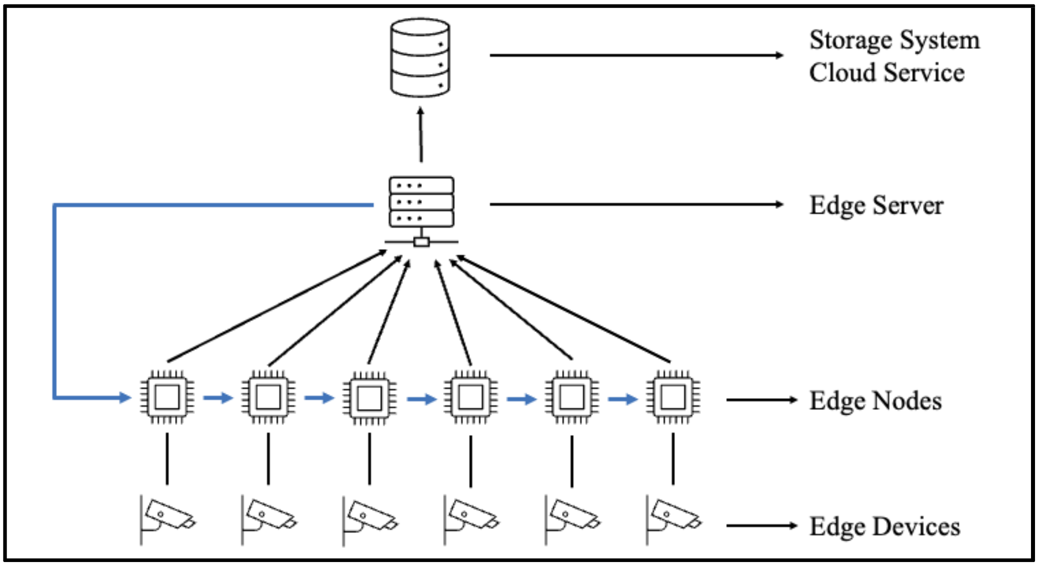
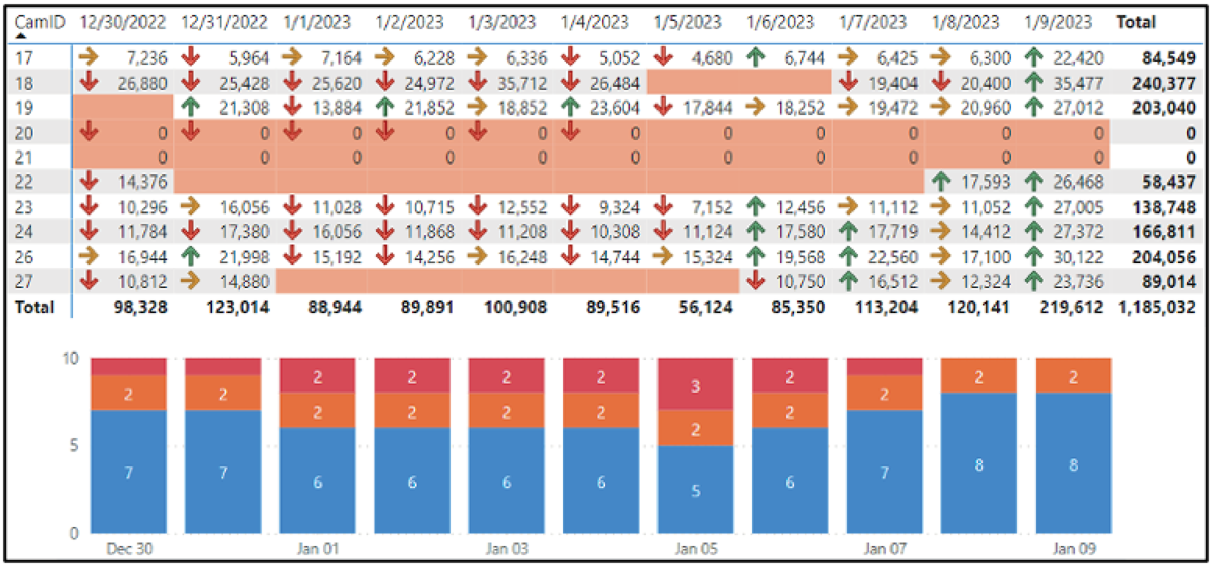


Figure 2: Edge computer system framework designed for high-throughput phenotyping in a farm environment.

In our experiment, the edge devices were set to save four images, depth, infrared, and colored (RGB) images, every five seconds while the animal drinks. All images collected from 0700h to 1900 h were saved locally on the edge node and transferred to a local private storage system. To minimize the amount of data transfer from the edge node to the edge server, all images are compressed into a 'tar.gz' file every 24 hours. The system generates a daily report for each edge device, which includes the device's name, disk space used, and the number of images collected. The reports are transferred to the edge server along with the compressed image files. The edge server controls the data transfer such that only one edge node can send data to the edge server at a time. We use a ‘plain text’ file named ‘transferqueue’ for this data transfer, which contains the edge device name and the authorization transfer protocol. Therefore, after the first edge node finishes, the next edge node is authorized to send data until the last edge node finishes the data transfer. The data transfer in our research experiment is executed at night to avoid network latency issues during peak hours. Finally, the reports generated by each edge node are combined and sent to the cloud to create a dashboard to monitor the edge system (Figure 3).

Discussion and future directions

Our primary goal was to develop an edge computing system capable of video-imaging dairy heifers in farm environmental conditions. The edge system with 29 edge devices (3D cameras) was successfully deployed on the farm, which started collecting images in November 2021. During this period, approximately 130 TB of daily images from 200 dairy heifers were collected and stored in a local private storage system. Each camera generates about 10.3 GB of images daily, compressed in a single file, which results in approximately 300 GB per day. An average of 3.47 MBps network bandwidth would be required to upload this amount of data to a cloud system within 24 hours. Even though the edge computing system was not sending images to the cloud, an important feature is the ability to create reports sent to the cloud and used to monitor the system (Figure 3). For example, if an edge node was not recognizing the edge device, an edge node was not connected to the Wi-Fi, or the edge node was not up and running. In addition, based on the report generated by the edge system, the number of images, size of data, and disk memory used could be monitored daily.



CamID	12/30/2022	12/31/2022	1/1/2023	1/2/2023	1/3/2023	1/4/2023	1/5/2023	1/6/2023	1/7/2023	1/8/2023	1/9/2023	Total
17	→ 7,236	↓ 5,964	→ 7,164	→ 6,228	→ 6,336	↓ 5,052	↓ 4,680	↑ 6,744	→ 6,425	→ 6,300	↑ 22,420	**84,549**
18	↓ 26,880	↓ 25,428	↓ 25,620	↓ 24,972	↓ 35,712	↓ 26,484			↓ 19,404	↓ 20,400	↑ 35,477	**240,377**
19		↑ 21,308	↓ 13,884	↑ 21,852	→ 18,852	↑ 23,604	↓ 17,844	→ 18,252	→ 19,472	→ 20,960	↑ 27,012	**203,040**
20	↓ 0	↓ 0	↓ 0	↓ 0	↓ 0	↓ 0	0	0	0	0	0	**0**
21	0	0	0	0	0	0	0	0	0	0	0	**0**
22	↓ 14,376									↑ 17,593	↑ 26,468	**58,437**
23	↓ 10,296	→ 16,056	↓ 11,028	↓ 10,715	↓ 12,552	↓ 9,324	↓ 7,152	↑ 12,456	→ 11,112	→ 11,052	↑ 27,005	**138,748**
24	↓ 11,784	↓ 17,380	↓ 16,056	↓ 11,868	↓ 11,208	↓ 10,308	↓ 11,124	↑ 17,580	↑ 17,719	→ 14,412	↑ 27,372	**166,811**
26	→ 16,944	↑ 21,998	↓ 15,192	↓ 14,256	→ 16,248	↓ 14,744	→ 15,324	↑ 19,568	↑ 22,560	→ 17,100	↑ 30,122	**204,056**
27	↓ 10,812	→ 14,880						↓ 10,750	↑ 16,512	→ 12,324	↑ 23,736	**89,014**
Total	**98,328**	**123,014**	**88,944**	**89,891**	**100,908**	**89,516**	**56,124**	**85,350**	**113,204**	**120,141**	**219,612**	**1,185,032**

Figure 3: Snapshot of the dashboard based on the daily reports generated by the edge system. Green, red, and orange arrows on the top of the snapshot indicate if a higher, smaller, or the same (approximately) number of images, respectively, were collected on that day compared to the average number of images collected in the last seven days. Bars at the bottom indicate the number of edge nodes that collected images on that specific day (blue), the number of edge nodes that were not connected to the edge device (orange), and the number of edge nodes that were not connected to the Wi-Fi (red).

Edge computing in livestock has been developed and used for multiple purposes in poultry (Yang et al., in 2019; Debauche et al., 2020a) and cattle (Bhargava et al., 2016; Caria et al., 2017; Alonso et al., 2020; Debauche et al., 2020b). However, such edge systems were developed for a single goal which may preclude their use for a broad usage across livestock species. For example, the edge systems proposed to date are based on

Raspberry PI or other microchips that, even though they are more affordable when compared with Nvidia Jetson Nano, have a different processing power to perform real-time image inference and pre-processing. This is an essential feature that the edge system based on Nvidia Jetson Nano presents since the model training or retraining can be performed on the edges without the need to transfer the data to the cloud over the network.

The edge system developed in this study has the potential to be used beyond video-imaging dairy heifers due to the system's flexibility. Wearable sensors can be connected to the edge node, in addition to camera devices, collecting real-time information from the environment, such as temperature, humidity, and gases. Further, the edge node can be used to record animal activity, rumination, and body temperature, among other parameters generated by wearable sensors attached to the animals. However, the Nvidia Jetson Nano's capability of recording and processing data from multiple technologies simultaneously must be further investigated. An alternative for overload in the edge node would be adding a central server equipped with CPU and GPU memory capable of processing the data locally. In addition, the lifetime and maintenance or replacement cost of such single-board computers must be investigated.

Combining edge computing, sensing technologies, and machine learning techniques offer many possibilities for real-time data generation, processing, prediction, and automation (Debauche et al., 2020a). Additionally, the ability to summarize and present this information in a dashboard-like format accessible through a mobile application can be essential for technology adoption. This allows farmers to visualize signals and alarms if the parameters are outside normal or acceptable ranges or even predicted by the system. Such multi-dimensional sources of information can help farmers have a more holistic view of the animals, ultimately leading to increased farm productivity and profitability, improved animal health and welfare, and reduced environmental impact. However, many of these features and possibilities are not yet implemented in the edge computing systems developed for precision livestock farming (Bhargava et al., 2016; Caria et al., 2017; Yang et al., 2019; Alonso et al., 2020; Debauche et al., 2020a; Debauche et al., 2020b), including the one proposed here. Therefore, there is a need to incorporate these features and possibilities to make the edge system more broadly applicable across different livestock species. The development of edge computing will be disruptive for precision livestock farming which can accelerate the application of precision technologies on a large scale.

Conclusions

The low-cost edge-computing systems for video-imaging livestock animals developed and implemented here successfully achieved our goal. We demonstrated that low-cost edge computing could be used to effectively video-imaging dairy heifers daily. Further implementations need to be developed for a fully applicable system to collect multiple sources of information besides images. These parameters will be relevant for various farm applications that deploy edge computing in their environment condition. This paper will open new frontiers for further development and application of edge computing beyond dairy operations to improve animal production, health, and welfare and mitigate livestock farms' environmental impact. Finally, the development of edge computing will foster high-tech innovations in the livestock sector, making significant changes for the farmers.

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