Conceptualizing a holistic smart dairy farming system

Leveraging sensor fusion and AI to the benefit of humans and animals

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Abstract: With the increasing use of sensor technology and the resulting diverse data streams in dairy farming, the potential for the use of AI rises. Beyond the AI-based solution of individual problems, a holistic approach to smart dairy farming is necessary. In this contribution, we identify and analyse a set of diverse use cases for smart dairy farming: lying behaviour analysis, heat stress monitoring, work diary, barn and herd monitoring, and animal health tracking. These focus both on animal health and welfare as well as assistance for farmers. Based on the requirements of these use cases, we design a holistic smart dairy farming system in an iterative development process.

Keywords: sensor integration, computer vision, assistance system, dairy cow monitoring, animal welfare

1 Introduction

Dairy farming entails many challenges for both humans and animals. On the one hand, farmers must perform physically demanding tasks, ensure the profitability of their farms and bear responsibility for the health of their animals [Ko13]. On the other hand, dairy cows achieve peak performance while exposed to risks of disease [Vo09] or hot weather periods [We03]. To meet these challenges, there has been an increase in technology adoption ranging from automatic milking and feeding systems [Ma19] to ruminal bolus sensors [HKV22] and activity trackers [ZWV19]. Thus, an artificial intelligence (AI)-based data analysis of the generated data streams has high potential. To ensure that this does not solely solve individual use cases in isolation, a holistic approach to the digital barn is called for. This constitutes the main motive of our research project, which integrates multiple sensor streams and tackles a diverse set of use cases. These use cases

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were selected based on consortium expertise as well as expert input and include *(A) lying behavior analysis* and *(B) heat stress monitoring* in terms of analyzing specific animal behavior. On top of that, we focus on providing a *(C) work diary* and a *(D) barn and herd monitoring* solution for the farmers. Lastly, we tackle overall *(E) animal health tracking* to provide extensive documentation and a starting point for multivariate predictions to support farm management. These use cases require the analysis of various data and sensor inputs as well as sophisticated means to extract relevant actionable knowledge. Thus, we define the following research question:

How can a holistic smart dairy farming system be conceptualized?

In order to address this research question, we analyze the five use cases tackling animal health and welfare, support for the work of farmers as well as documentation of the animals' condition. Our system design concept is comprised of a technical architecture including hardware as well as software. It is geared towards integrating the analyzed use cases, handling vast data streams from multiple sensors including cameras and microphones as well as delivering relevant information and support to the farmers.

In the following, we will first present related work regarding assistance systems in livestock farming and AI-based dairy farming solutions. We then describe our research methodology, the design science research approach. Next, we provide a systematic analysis of the five use cases followed by the derived concept for a holistic smart dairy farming system. Finally, we discuss our results and provide an outlook for future work in research and practice.

2 Related work

Current scientific discourse recognizes the potential of AI – for agriculture in general and dairy farming in particular – and drives innovation by developing relevant AI-based solutions. Not only the analysis of structured data, but especially the evaluation of image and video data – namely, computer vision – has a major impact in this domain. For example, the prediction of body weight and body condition scores can be automated [Ru20]. On top of that, different approaches for tracking cow activities have been proposed. Among these are solutions that focus on tracking the animals' position in different areas of the barn [SK21], the animals' feeding time [PF18], their lying behaviour [Po13] and their rumination activity [So19]. But the analysis of social interactions within the herd is also of interest [SK20]. Another current research problem in this domain deals with cow identification in order to track the behaviour and state of individual cows. Approaches range from face recognition [We22] and muzzle characteristics [KC18] to methods based on coat patterns in spotted cattle [Ta21]. A major concern in AI-based animal monitoring is animal health. For example, lameness can be detected early when using anomaly detection on pedometer data compared to visual inspection by farmers [By19]. For dairy cows, particular health-related developments are especially important to understand. These include the detection of heat stress [Be21] and the gain of reproductive health information such as diagnosing mastitis [Ka22], predicting calving [Ca08] and detecting oestrus [Gu19]. Of course, information related to economic efficiency is also relevant, such as predicting milk yield [Li20]. In order to obtain the necessary data for AI-based dairy farming, research is using cameras and especially depth cameras, microphones, as well as sensors placed on and inside of the cows. The methods for data analysis range from decision trees to deep convolutional neural networks.

However, as sophisticated as these solutions are becoming, they need to be integrated into a holistic system for smart dairy farming to reach their full potential. On the one hand, this requires the integration of diverse data sources as they provide the best results for specific use cases, e.g., when detecting diseases in cows [La21]. On the other hand, this should include the integration of diverse use cases in order to provide a truly useful and easily manageable tool to farmers. This issue will be addressed in our contribution as we selected a set of five diverse use cases to be analysed by experts and integrated within a technical framework.

3 Research approach

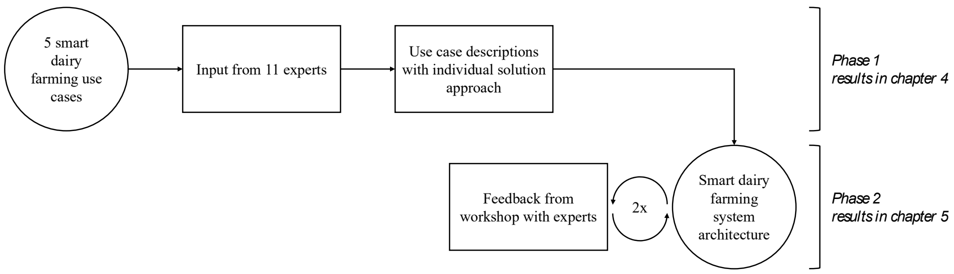

Fig. 1: Research approach

To analyse use cases and design a solution approach, we carried out our research in two phases that are visualized in Figure 1. In phase one, we conducted interviews with 11 experts. The experts, their company or institution and expertise as well as the content of the interviews are described in Table 1. Based on these interviews, we identified relevant use cases as well as the current practice regarding the use cases, and requirements for an AI-based solution as well as a solution approach. In phase two, we developed a hardware and software architecture for a holistic dairy farming system over the course of an iterative development process. The first draft was designed based on the interviews and evaluated with a group of four experts for AI engineering and assistance systems. The resulting draft was evaluated in turn by two experts currently engaged in developing other smart dairy farming solutions. This evaluation resulted in the final architecture presented in this article.

No.	Company or Institution	Expertise	Content of the interview
1	Research Institution A	Expert for digital monitoring of human health	Interface design, handling of streaming data, potential for explainability
2	Research Institution A	Expert for intelligent assistance systems	Interface design, potential for learning purposes
3	Farm B	Animal husbandry worker	Current practice and potential for AI in daily activities, requirements for assistance system
4	Farm B	Herd manager	Current practice and potential for AI in daily activities, requirements for assistance system
5	Farm C	Herd manager	Current practice and potential for AI in daily activities, requirements for assistance system
6	Public Institution D	Official Veterinarian	Current practice and potential of AI for detecting health problems in cows, application of assistance systems with the involvement of veterinarians
7	Public Institution E	Work scientist and expert for digitilization in animal husbandry	Current practice of AI in farming and work science, requirements for management support
8	Farm F	Animal husbandry worker	Current practice and potential for AI in daily activities, requirements for assistance system
9	Farm F	Herd manager, advisor for projects in animal husbandry	Current practice and potential for AI in daily activities, requirements for assistance system
10	Farm F	Expert for digitalization in animal husbandry	Current practice and potential for AI in daily activities, requirements for assistance system
11	Farm F	Expert for digitalization in animal husbandry	Current practice and potential for AI in daily activities, requirements for assistance system

Tab. 1: Description of the interviewed experts

4 Primary use cases in the smart dairy farming system

Five use cases have been identified as most relevant and realistic for achieving a smart dairy farming system. The selection was based on the expertise of the consortium as well as the input from the experts described in Chapter 3. Table 2 describes the five use cases, names the proposed area of support for the farmer, and gives examples for the expected output. As a result, dashboard visualisations of events and recommendations for action will support the farmer to detect health problems earlier and make farm management more efficient. Use case (A) for example is aiming to analyse the lying behaviour of the cows. The process of lying down gives information about the barn design, but also if the animal has health problems such as pain in the joints or lameness. The smart farming system aims to monitor the process continuously and send an alarm in case of abnormal behaviour.

Use Case	(A) lying behaviour	(B) heat stress monitoring	(C) work diary	(D) barn and herd monitoring	(E) animal health tracking
Brief des-cription	Analyzing lying process, deriving infor-mation on barn design, comfort, hygiene and indicators for health problems	Recognition of heat stress indicators in animal behaviour and recommen-dations for counter measures	Record of productive times and ancillary for efficient management, monitoring of health and safety issues of workers	Review of current activities and status of the barn, visual barn representation for the farmer with added information from other use cases	Recording health parameters for each animal and the herd continuously, relevant data is bundled in one place, automatically forwarded when necessary and used for predictions
Area of support	Animal health	Animal health	Farmer assistance	Farmer assistance	Documentation, animal health
Solution approach	Determine the lying times, aggregate information on lying time and lying-down process	Tracking animal locations and activities in the barn, measuring temperature and humidity	To do list, anonymized recognition and registration of task fulfilment, visual representation of completed activites	Animal tracking, barn evaluation to support task management, temperature control or health care issues	Interfaces to existing systems, track individual animals, aggregate herd health, manual entry of relevant data if necessary, contact to veterinarians for emergencies
Output	Dashboard with lying times and duration	Dashboard showing heat stress indicators	Record of work activities, entry in database, visualization for the user	Dashboard showing live position of animals, warning in case of abnormal events	Dashboard, digital health record for the individual animal/herd, warning system
AI functions	Cow detection, pose estimation, pose classify-cation, ergo-nomic analysis and anomaly detection of lying behaviour, box detection, box status classification	Cow tracking and identification, activity classify-cation, anomaly detection of activity patterns, classify-cation of heat stress behaviour, weather data analysis, heat stress prediction	Human pose-esti-mation, anonymi-zation, ergonomic analysis during tasks, recognition of performed tasks, time analysis, classification of human-animal-interaction	Cow detection and tracking, cow identification, activity classification, anomaly detection of activity patterns, herd interaction recognition, anomaly detection of herd interaction	Ergonomic analysis of cow movement, anomaly detection of activity patterns, anomaly detection of health parameters, illness prediction

Tab. 2: Use case descriptions

5 Designing a holistic smart dairy farming system

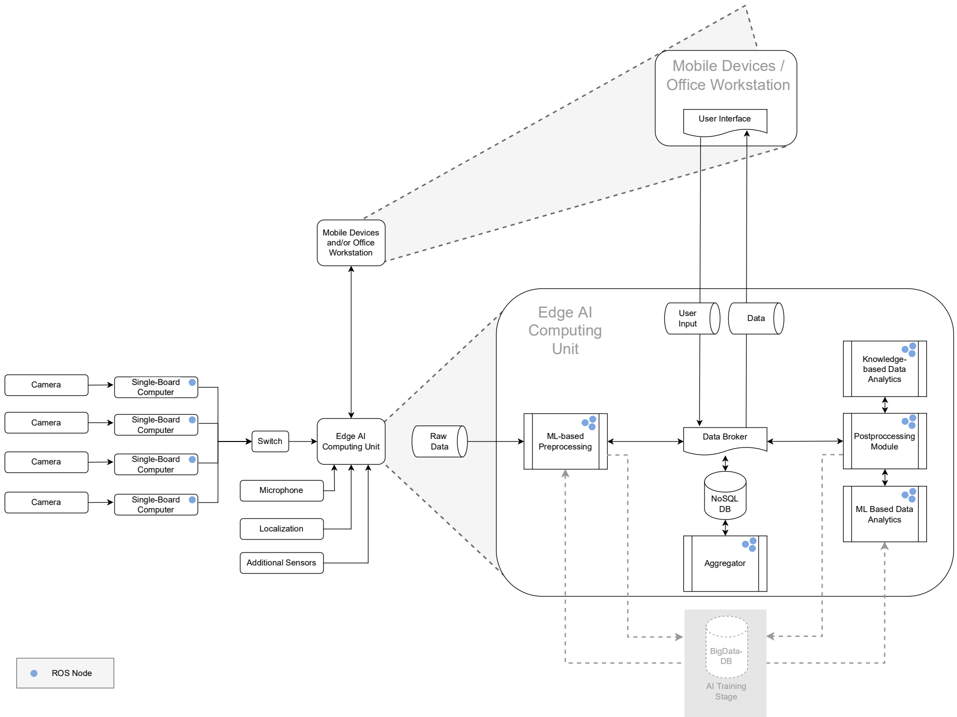

Fig. 2: Architecture for the smart dairy farming system

The derived architecture of our holistic smart dairy farming system divides itself into hardware and software components. Figure 2 gives an overview of the system, where hardware components can be seen on the left side of the figure and software components are depicted in relation to the corresponding hardware parts in the right of the figure. Overall communication between components will be realised with the Robot Operating System (ROS). Below, first the software and then the hardware components of the architecture are described in detail.

In terms of software, the first module of our ROS-based implementation is the Machine-Learning-based pre-processing, consisting of several ROS-nodes used for the pre-processing of raw input data of all sensors. This includes the sensor integration of the used sensors, Machine Learning algorithms for cow detection and tracking as well as cow identification, activity classification of cows, box condition classification, pose estimation of animals and humans as well as tracking human-cow and cow-cow interaction. The refined information generated by the Machine-Learning-based pre-processing will be passed over to a data broker handling all information flows of the edge AI computing unit. The data broker administrates communication with a NoSQL database, a post-processing module, and a user interface. Incoming information is stored in the NoSQL database, and requests from the user interface are followed by the provision of relevant information stored in the database. An aggregator module is continuously running on the data stored in the database and provides temporal aggregation. For example, a summary of information on the position of animals resulting in overall length of stay by the drinking trough, walkways, lying boxes and feeding table for different time intervals like days, weeks, or months. The post-processing module administers both the knowledge-based data analytics and Machine-Learning-based data analytics. The post-processing is responsible for all data analytics on refined data relying on the knowledge-based data analytics for expert knowledge, and on Machine-Learning-based data analytics for predictions or anomaly detections. While analytics of lying times of specific cows or the whole herd would be compared with desired lying times for cows in the knowledge base, an anomaly detection of lying times would be conducted in the Machine-Learning-based data analytics. As no raw data is stored in the NoSQL database, a second database is needed for the training stage of all Machine Learning algorithms. The big data database is depicted in light grey in Figure 2 to illustrate that it will not be part of the operative smart dairy farming system but rather be used for training purposes. The Flutter-based user interface will be able to run on any mobile or stationary device the user chooses, offering the opportunity to use the system while walking through the barn or from a desktop PC sitting in the office.

In terms of hardware, the project utilizes the Intel RealSense D455 Depth Camera to obtain a live picture stream of red, green, blue and depth (RGB-D) information in the barn. It captures RGB images at a resolution up to 1280 x 800 at a frame rate of max. 30 frames per second (fps). The depth data has a resolution of 1280 x 700 and a frame rate of max. 90 fps. It is created by an infrared emitter, which projects a pattern into the barn. Thereby, the stereoscopic depth camera can reconstruct a depth image. The RealSense vision processor D4 merges the RGB and depth images and provides data via a SuperSpeed USB 3.1 interface. For high data rates, the USB 3.1 specifies cable lengths up to 3m or max. 5m. Active extension cables or optical USB extension cables can overcome this limitation but need an energy supply at the devices' end of the USB cable i.e., at the cameras in the barn. Due to deployment limitations in the barns, which are constantly populated with living cattle, the project aims at using low-voltage installation. Therefore, we decided on the distribution of camera nodes via Power over Ethernet (PoE+ IEEE 802.3at) connection, which provides a low voltage, 48V/25W energy provision whilst enabling gigabit ethernet connection. For integration into the Architecture, every camera node is equipped with a Raspberry Pi 4 single-board computer (SBC), which enables the provision of the USB-based camera functionality in the network [Op22]. However, this solution results in a reduction of available RGB-D picture resolutions or a reduction of fps due to bandwidth limitations. Since the project is not aiming at high-speed object detection and since the cattle are moving at a limited speed, a framerate reduction seems feasible. For installation purposes, we developed a parameterized 3D-model that can be printed via fused deposition modelling (FDM) to provide a long-term reliable mount of the camera, a Power over Ethernet splitter and the SBC. It is designed in OpenSCAD and accepts parameters for camera position, pitch, roll and azimuth. Thereby, a customized mount can be printed after measuring this parameter set and cameras can be installed securely in any position. In addition to the image data, further heterogeneous sensors are used in the project. In particular, the localization of individual animals is provided by a bluetooth (BT) 5.1 angle of arrival (AoA) indoor localization solution. Depending on the size of the barn, a set of 4-8 BT AoA antennas is installed to track collar-mounted tracking tags that provide the location of individually identified cattle as a ground truth for the AI. Distributed microphones are used to monitor the noise level and to identify individual cattle sounds that may support the detection of situations like heat stress. To enable a holistic sensor fusion, we aim to develop interfaces to existing sensors and other technology in the barns, e.g., cooling fans, brushes, and milk robots. Ideally, this would include all available sensor information and result in a fully integrated assistance system.

6 Discussion and outlook

In order to address our research question – *How can a holistic smart dairy farming system be conceptualized?* – we selected a diverse set of dairy farming use cases, conducted expert interviews to analyze these use cases and subsequently developed a solution concept for an AI-based dairy farming system. This concept was derived through an iterative development process and illustrates the hardware and software architecture of the intended smart dairy farming system. The hardware architecture integrates different sensors ranging from cameras and microphones to localization tags and enables edge AI computing with an approach suitable to a barn. The software architecture consists of two main stages and is geared towards efficient data processing and combining both machine learning and expert knowledge. In stage one, raw sensor data is streamed and analyzed to obtain relevant metadata. Especially, computer vision techniques are utilized to extract structured data from images. For example, pose estimation is performed on images of cows during a lying-down process, and pose coordinates are saved. In stage two, high-level information and recommendations for action are derived from the obtained metadata. For example, machine learning can be used to recognize anomalies in lying-down behavior that might coincide with relevant issues such as lameness or unsuitable lying box conditions. On top of that, expert knowledge can be used to recognize issues in lying down time when certain stages of the lying down process exceed defined standards. Taking into account a set of diverse use cases enabled us to design a holistic concept for smart dairy farming systems. As opposed to optimizing a solution to an individual problem in dairy farming, this system is aiming to integrate multiple sensors and create a consolidated assistance system for farmers.

However, the objective of a holistic smart dairy farming system is accompanied by three major challenges. Firstly, the multi-sensor setting including depth cameras produces an extremely large amount of streaming data that needs to be handled. Analyzing such a large volume of image data through computer vision and integrating several camera perspectives requires efficient algorithms and sufficient computing power. Secondly, the process of multi-sensor integration itself is far from trivial [Zh18]. In terms of image data streams in our application scenario, cow movements must be tracked, poses estimated, and individual cows identified based on several cameras covering different areas of the barn, missing some parts of the barn entirely and overlapping on others. On top of that, the other sensor inputs such as microphones need to be integrated as well. Therefore, producing a consolidated set of metadata for the barn based on the sensor information is a crucial step in implementing an effective assistance system for the farmers. Thirdly, in order to fully deliver on the promise of a holistic smart dairy farming system, interfaces for the existing technical infrastructure already installed in the barn and software solutions already used by the farmer need to be established. Otherwise, farmers would still need to keep track of the unintegrated infrastructure by themselves and have to interact with a large number of applications. Tackling these practical challenges will be part of our future research and implementation process.

In the future, we plan to focus on the technical implementation as well as practical evaluation in an iterative process. The developed concept constitutes a blueprint for successively implementing individual functions that may each be utilized in multiple use cases. Naturally, implementation will start at stage one, i.e., extracting metadata and later advance to stage two when metadata streams are available for analysis. Initially, we will address the described use cases. In the long run, a smart dairy farming system would benefit from including an even broader range of use cases. In addition to the technical developments, there will be a continuous evaluation with the help of two farms using the provided solution and guiding its evolution. The application of the smart dairy farming system raises several research questions to be tackled in the future. For example, expert knowledge should not only be integrated into the system through domain standards translated into rules in the knowledge base. Ideally, farmers using the system and giving feedback on recommended actions or correcting false predictions would also have an impact on future Machine-Learning-based outputs. At this point, only few approaches to human-in-the-loop systems and feedback learning exist in the domain of dairy farming [Ta20]. On top of that, providing a personalised interaction for different farmers would be an important feature of the smart dairy farming system [MFH09]. As users might have varying experience levels in farming as well as with AI-based assistance systems, their needs for detailed information and their amount of time available when interacting with the system might differ. Another success factor of smart dairy farming systems is user acceptance. This might be impacted by numerous design choices and needs to be prioritized in the development process. For example, providing the farmers with relevant and easily understandable explanations for the AI-based recommendations and predictions might help to reduce negative attitudes towards AI and improve farmers' decision-making process [Ha22]. On top of that, the interviews revealed that installing cameras in the barn might negatively impact farmers acceptance as this could be interpreted as a measure of surveillance. Thus, human-centered strategies are necessary that ensure privacy and still enable the extraction of data used to help the farmers manage their tasks. These topics are important areas of research we will take into account during the further development of our smart dairy farming system.

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