Towards animal welfare monitoring in pig farming using sensors and machine learning

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Abstract: Animal welfare monitoring has the potential to improve animal welfare and provide quality-oriented differentiation for producers at the same time. However, early approaches to animal welfare monitoring use manual injury scoring and evaluation of slaughter data and other biological data. These approaches are often characterized by manual data collection, with data being evaluated infrequently. Thus, production costs would increase substantially. However, with the advent of high-tech commercial sensor technology, monitoring can be conducted automatically, objectively, and at low cost. The aim of this study is to review the suitability of environmental sensors in combination with machine learning in an intelligent animal welfare monitoring system. The system automatically analyzes data from commercially available low-cost sensors, identifies animal welfare risks and recommends actions for animal welfare.

Keywords: Animal welfare monitoring, environmental sensors, machine learning

1 Introduction

Animal welfare is gaining importance due to value changes by consumers [We16]. These value changes have the potential for price diversification of the meat industry [NGB10]. One economically sustainable option to animal welfare is animal welfare monitoring [JMA17]. Animal welfare monitoring refers to internal company control by suitable animal welfare indicators.

Previous research on animal welfare indicators has focused mostly on the development of guidelines for manual internal monitoring [Za17]. So far, these animal welfare indicators have evaluated injury scoring, slaughter data and other biological parameters [Kt16]. However, such manual animal welfare indicators are sometimes only evaluated every six months and increase production costs [Kt16].

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Sensors to generate the necessary data are commercially available and are in use in other industry sectors. Thus, for example, 2D cameras, microphone systems and other environmental sensors for recording the housing environment are available (e.g. CO_2 and NH_3). These sensors can be used to detect behavioral changes, e.g. reduced animal activity, water consumption or food intake indicate animal welfare risks [Ma16b; WHK09]. Such behavioral changes can be identified with suitable sensors for animal groups [MK05; Ma17a].

Machine learning algorithms are particularly fit for the automatic analysis of sensor data, since large volumes of data increase their performance [Mi97] and deep learning algorithms can also adapt to unstructured data [LBH15]. However, these methods are largely unexplored in pig farming [KP18].

2 Material and methods

This study is based on the Boxberg Teaching and Research Centre – Centre for pig rearing and pig breeding (LSZ). The LSZ has about 3,500 animal places (pigs) in conventional and alternative breeding methods and an attached slaughterhouse. By selecting this research facility, data from routine operations is available (e.g. feeding, temperature, sow planner and slaughter data). In addition, databases of specially used experimental equipment (e.g. video, RFID, motion loggers) can be accessed from current and completed trials.

Currently, in pig husbandry mainly climate and environmental data (such as air temperature, noxious gas concentration or brightness) and system data (electricity or water meters) are recorded, while sensors for individual animals are rarely used due to the short life of the animals and the relatively high costs [HH19].

Environmental sensors including climate and water quality are important features that directly affect each animal in a pen. In addition to temperature sensors, other environmental parameters include harmful gas sensors for controlling ventilation [MHH06]. Thus the climate of the stable is determined by the factors temperature, humidity and velocity of the air as well as harmful gas concentrations (CO_2, NH_3, H_2S). Commercial sensors for the continuous detection of these environmental parameters are available.

Using video cameras, 3D cameras and deep learning, the position of pigs can be detected [Ma17b; Pe18; Va17]. Movement and recumbent behavior can be evaluated from the data, and modern deep learning methods allow the transfer of the detection system to other pens without reconfiguration of the algorithms [LBH15]. RFID can automatically monitor hotspots in a pen and provides specific data for each pig individually [Ad18; Ha16; Ha17]. For this purpose, readout antennas are attached to each monitored position (hotspot) [KAG18] and each animal is equipped with one to two ear tags with Ultra High Frequency (UHF) [Ma16a].

3 Results and discussion

Sensors are used at the LSZ Boxberg to examine and monitor environmental factors (including temperature, humidity, air velocity, harmful gas contents), which have an influence on animal behavior. For example, if the pen temperature rises on a hot summer day, then the feed per day of fattening pigs will decrease. The sensors are queried within an interval of 5 seconds. The measured values are retrieved via a programmable logic controller and transferred to a database. In a database, the values are stored only when the previous measurement value is changed. If a sensor fails, we receive an error message via email and the defective sensor can be replaced or repaired (approx. 250 sensors are currently in use).

In the LabelFit project, RFID was used at an activity tower to determine the frequency of visits to the tower. In the tower were different activity materials such as chopped straw or chopped straw with corn kernels. Another project involves behavior at the feeding trough or at the drinking trough. The aim of this research is to identify if there was an outbreak of tail biting before signs in the visiting behavior at the feeding trough or at the drinking trough.

With IP cameras (H.264) the behavior of sows, rearing pigs and fattening pigs is recorded. Depending on the size of the pen and the observed area, up to 4 cameras per pen are in use. The cameras are mounted on the ceiling or the compartment wall. The cameras should be at least IP 66 rated to withstand cleaning and disinfection after each run. PoE (Power over Ethernet) cameras were rarely used, because of the long cable ways a power cable was used instead. PoE, however, simplifies installation of the cameras in the compartment.

Detecting animal welfare risks is addressed by a supervised learning task [Va00]. In supervised learning, a machine learning model is trained to map $(x \rightarrow y)$ an input x (features) to an output y (target variables) by previously generated examples of input x and output y [Va00]. In this setting, the aim for machine learning is to inform the farmer at an early stage of behavioral deviations and animal welfare risks (output y) by using available sensor data (input x).

Temperature, CO_2 and other structured sensor data can be preprocessed for usage as machine learning features (input x). However, unstructured sensor data (e.g. RFID, cameras and microphones) will have to be transformed into structured time series data concerning animal behavior (e.g. lying time and hot spot activity). First approaches to transform unstructured data into structured data already exist (e.g. pig position detection from video cameras [YXL18] or RFID hotspot detection [Ad18]).

Finally, combining animal behavior with structured environmental sensors (e.g. potions, air quality, and temperature) can produce predictions about target variables (output y) like production conditions (e.g. cough, lameness, diarrhea, fever), behavioral disorders, errors of the ventilation system and stress potential. The most practical target variables (output y) will be variables that are already recorded. This includes medication, injury scoring, weights and slaughter data. Prediction of these variables early on will allow for better animal welfare and reduced documentation tasks for the farmer. An overview of current machine learning algorithms for sensor data is given in Tab. 1.

Features (input x)	**Feature type**	**Target variable (output y)**	**Machine Learning algorithms**
2D video images	Unstructured data	Lying and feeding behavior	Deep Learning, object detection [YXL18]
CO2, lying behavior, feeding behavior and live weights	Structured time series data	Medication, injury scoring and slaughter data	Linear SVM, Random Forest and Linear Regression [Zi20]

Tab. 1: Machine learning approaches for sensor data

A limitation for usage of machine learning in pig farming is the availability of interlinked sensor data and the necessity for manual individual data cleansing, because of the quality of the currently available target variables (output y). Interlinked and clean data can be achieved by a data platform. Such a data platform achieves this by automated Extract, Transform and Load (ETL) processes, which allows for automated application of the machine learning models in practice. Currently, in pig farming, the availability of data platforms with digital data collection and aggregation is limited [Da19]. Recent work has begun to develop such a data platform [HR18].

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