Can AI imaging technology be used for monitoring specific behaviours in broiler flocks?

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Abstract

Commercial poultry production, e.g. optimum bird growth, requires an optimally controlled environment, which is currently based upon temperature, humidity, CO2 and air pressure, whilst water and feed consumption are also measured.
PLF systems exist to monitor (reduced) movement or change of positioning of the broilers in the house, However, other parameters related to animal welfare and health such as feeding, drinking and movement behaviour are still largely dependent on visual observations by the stockman 2-3 times a day when the flock is checked. This not only relies on the quality of the observations by the stockman, but also doesn't guarantee fast, effective management of the flock.
Automated 24/7 visual monitoring of broiler flocks using Artificial Intelligence (AI) imaging technology to classify specific behaviours in real time might provide unbiased information relating to health and welfare of the flock. Small changes in behavioural observations might lead to early detection of disease and optimized climate control.
A current feasability project has started to test which behaviours can be identified using AI technology and how these quantified behaviours could be used to optimize health and welfare of the flock being monitored.

Keywords: poultry, broilers, artificial intelligence, behaviour, labelling

Introduction

Poultry meat consumption worldwide has increased worldwide and compared to beef and pork is requires less environmentally damaging inputs (FAOSTAT, 2015). In general, commercial poultry meat production uses large houses with tightly controlled indoor environments to grow broiler chickens at high stocking densities. The management of the birds focusses mainly on keeping environmental parameters, temperature, humidity, carbon dioxide, air pressure and ammonia and production targets, e.g. water and feed consumption within tight margins. Automated climate control systems and remote monitoring services (OptiFarm) assist the farm managers with this process (Wathes et al., 2008).
Relatively small deviations from the optimum environmental climate cause significant changes to the chicken’s behaviour and wellbeing, with stress a major contributor to mortality and morbidity. Observations of behaviour(s) are a proven indicator of animal health and welfare (Abeyesinghe et al., 2021), both positive and negative. Small changes in the behaviour of individual chickens and/or the flock, often reduced movement or a change in position within

the house, can be indicative of the onset of disease or another ailment (Colles et al., 2016; Dawkins et al., 2012).

Farmers have limited resources to monitor behaviour other than through the twice daily visual inspection of the birds. Camera based systems such as EyeNamic provide information on general bird activity and distribution and have been linked to welfare status (Peña Fernández et al., 2018) whereas the OptiFarm monitoring service uses the real-time camera images to check for major issues only.

Whilst it is not possible to track and identify the behaviour of all individual birds in the house, it might be possible to identify the behaviour of birds at a specific time point. A new project aims to record which set of behaviours are being displayed by which proportion of birds at specific times during the day and will also include current environmental conditions.

Automated welfare monitoring using camera systems offers more to the industry than simple visual benefits, providing quantified data assessment of health and welfare of chickens. This assessment would benefit individual partners through improved performance and thus profits.

Material and methods

Data annotation is the process of applying labels, whether automatically or though manual operations, in order to generate samples of accurate results expected of a well-functioning AI model. These samples are known as ground truth data. Ground truth, or training data, encompasses the total knowledge of a machine learning model in a specific domain.

The creation of training data requires the right tooling, and the right talent to use such tools. In most cases it involves experienced labelers applying tags, bounding boxes, or encircling items with polygons on a graphical user interface. Furthermore, this system must follow an immutable yet comprehensive taxonomical schema that allows machine learning developers to train the various types of models expected in the project. The system must also be accessible via a web browser, synchronize globally across teams, and enabling an efficient review experience for stakeholders.

To build a data set of behavioural patterns throughout a broiler growing cycle short video clips (max 5min duration) will be taken at key moments in the growing cycle. For this purpose 2 GoPro7 cameras have been installed in one of the houses at a commercial broiler farm (64.000 birds per house) managed by Hudson & Sander (trading as Applied Poultry Group) and monitored by the OptiFarm service. Environmental data and issues and/or recommendation by OptiFarm data review experts will be recorded and stored.

The video will be cropped to a 4 m * 4 m square, which at the current stocking density will show approx. 250 birds at any time. For each video frame, the labellers will use the V7 annotation platform to perform a polygonal segmentation around each chicken, indicating their current behaviour with a tag. The use of polygon annotations, although more time consuming than bounding boxes, allows for the identification of individual chickens while clustered. A minimum of 400 instances of each behaviour over the duration of the crop will need to be identified and labelled. A larger number of labelled data will improve the AI model. This will generate a dataset where each chicken is in a behavioural state, enabling the AI to understand the visual differences between behaviours.

The specific behaviours selected for this feasibility study and deemed to provide a reasonable behavioural assessment are:

- eating
- drinking
- resting
- walking
- feather pruning
- wing flapping
- wing flapping and running

The wing flapping behaviour will not be seen till the birds are approximately 15 days old as around that time the wings are sufficiently developed and the birds start using them. Secondly, some of the behaviours will occur more often than others and will therefor require more footage to be reviewed to achieve an acceptable number of labelled incidents.

Although this technology to be used in this project as such is not new, the application of the technology is and uses the expertise of V7 in labelling and training the AI model(s).
The labellers will be provided with example behaviours generated by behavioural experts. Random samples of the labelled data will be expert reviewed.

Results and Discussion

The initial phase of the project has started and collection of video clips is currently underway and labelling is due to start shortly. We intend to present the results of the labelling and AI model training at the conference.

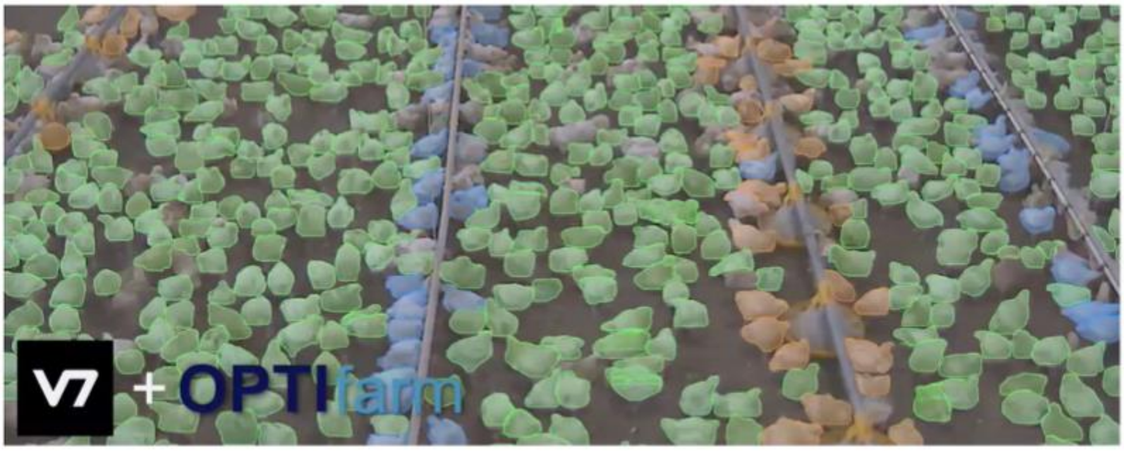

Figure 1: model identified behaviour based on limited preliminary data set with drinking chickens (blue), feeding chickens (orange) and moving chickens (green).

Preliminary work done before the start of the project is shown in figure 1. Here all birds identified by the AI model as drinking are shown in blue, those eating in orange and those moving in green.

The use of the polygon annotations clearly works well in identifying each individual chicken. The model identified most feeding and drinking birds well, but clearly has issues with distinguishing moving and stationary (resting) birds. This is largely due to the very limited data set available for labelling and training of the model.

Conclusions

Using existing artificial intelligence technology to identify specified broiler behaviours is eminently feasible provided the labelling and model training is appropriate for the dataset.

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