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Precision Livestock Farming IT Support Model for the Poultry Industry

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Abstract. The presented work proposes a practical approach to bird weight data processing and augmentation to enable production outcome forecast model training, which contributes to higher productivity. We suggest using the parametrized model, where parameter values are found through genetic optimization and thus are closely corresponding to broiler body weight factual measurements. The proposed approach is implemented as a stand-alone software system, exposing the models through containerized web services enabling different use scenarios.
Keywords: Precision Livestock Farming, Poultry, Parametrized Model.

1 Introduction

The global population is growing rapidly over the current period, and according to United Nations estimates [1], it is projected to reach 9.7 billion by 2050. Such an increase in population may have an impact on the sustainability of the demographic, social, and economic system. One of the biggest challenges in this context is the production of sufficient quantities of food, which in turn relates to agriculture, which must be capable of ensuring the required size of plant cultivation and poultry and livestock farming.

Poultry meat production plays an important role in food production, with global production of chicken reaching 100 million tons per year already and expecting a significant increase of it in the coming decade [2].

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In poultry business, profits are relatively small, and therefore even slight improvements in production productivity could significantly improve the profits of the producers. The strategy to achieve such productivity improvements is precision poultry farming. The concept of accurate poultry farming is related to the concept of Precision Livestock Farming (PLF) and means the automated or manual collection of data on the progress of the poultry production process, developing mathematical data models, and analyzing the relationship between the various factors affecting bird growth (breeding environment, feed recipe, welfare conditions, and other indicators) and different variations of the actual results aiming to identify optimal process conditions.

This article reports on the research and development of a cloud-based data collection and analysis tool prototype that will generate recommendations for optimal production environment parameters to increase the productivity of the poultry production process. To develop an IT support model for the poultry industry the following research questions are addressed:

RQ1. What is the research focus in PLF?
RQ2. What are the key environmental factors in the poultry industry?
RQ3. What models can estimate broiler growth?

The main contribution is the developed data collection system, parametrized broiler body weight forecast model that plays the central role in further developing machine-learning models for particular production control inputs.

In the article, Section 2 emphasizes the importance of the well-established production process in the context of production needs and discusses current research trends. Section 3 reports on the most important parameters and needs for poultry production control and current practices of their collection. Section 4 provides insight into the sample data collected during the practical problem exploration phase and a proposed parametrized broiler body weight forecast model fit on the collected data. Section 5 provides insight into the proposed and implemented data collection IT solution. Section 6 provides the main conclusion and our vision of the future work necessary to make the whole solution operational.

2 Relevance of the Problem

Precision livestock farming (PLF) is the use of information technologies for continuous and automated monitoring of animals and farms, which helps farmers detect problems as soon as they arise and improve animal welfare.

The concept of precision livestock farming was formed only in the 21st century when the first EU conference on precision livestock farming took place in 2003. The word “precise” within the PLF term means the management of the process. The main benefit of implementing the PLF system is ensuring that each process in a livestock enterprise, which may have a major positive or high negative impact on productivity and profitability, is always monitored and optimized within a limited range. PLF technology offers objective and automated measurements based on animal indicators and environmental data. Monitoring data are translated into key indicators of animal welfare, health, productivity, and environmental impacts.

As summarized by [3], PLF, in terms of measurements and process management techniques, concentrates on several key application areas: (1) water management, (2) food supply and consumption, (3) animal/bird behavior analysis based on image processing, (4) growth and weight control, (5) production monitoring and control, (6) environment and welfare management. Our efforts focus on the broiler body weight control as the main outcome parameter of the production process.

Besides in direct production management, the actual outcomes are heavily dependent on the birds’ health and welfare. In a modern production process, the change of generation in the herd is very fast – using modern production methods the target weight of birds is reached within 5–6 weeks. Therefore because of their rapid growth rate, broilers suffer from such problems as sudden death syndrome, ascites, and contact dermatitis [4]. Broilers are the largest population of birds worldwide, compared to any other farmed species, with up to tens of thousands of individuals per accommodation.

To address the current and future food security and sustainability of production issues, the number of research contributions to these domains is summarized in Figure 1.

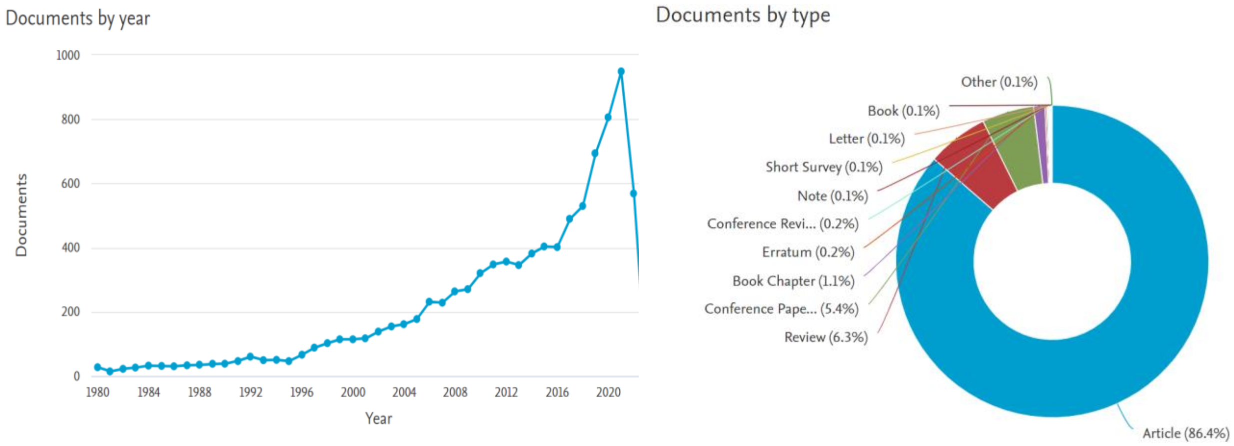


Figure 1. The number of articles per year and their distribution per type, SCOPUS cited on 27.08.2022

According to studies reported in [5] and [6], the main contributors to the scientific community are researchers from the countries that are the major producers and consumers of particular product types, which reflects an obvious interest of researchers to contribute to the economy of their countries.

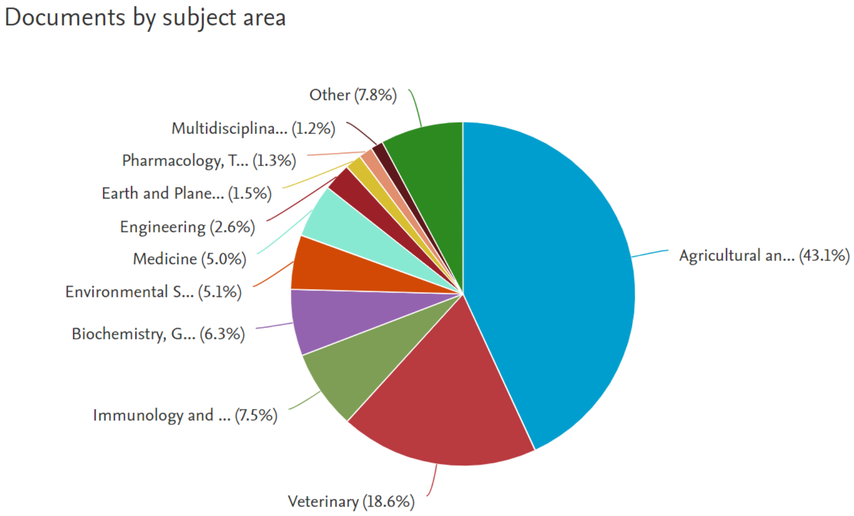


Figure 2. The relative number of articles per subject, SCOPUS cited on 27.08.2022

In PLF, various surveys have been carried out on poultry farms, analyzing the use of technology, particularly in the USA, China and Belgium. The studies have concluded that most technologies are still in the development phase (prototypes) and are not widespread [7]. Most studies describe prototype systems, but only around 4% describe commercially applied systems, and there is a significant market opportunity for PLF-supporting IT solutions. The same trend is reflected by the research subjects of the articles (see Figure 2), where only 2.6% are devoted to engineering.

3 Key Parameters and their Collection Means

Before defining particular models or solutions, it is important to identify the needed parameters as inputs for the models, i.e., what can be measured or estimated, and what are the means of data collection. Besides the mentioned, according to the current practices, some of the input data are collected manually with relatively low frequency leading to pure feedback or input data for the production control or decision support systems. Therefore, our approach is comprised of the selection of collectable indicators, model definition, and IT solution design to automate the data collection and model operation.

3.1 Key Environmental Parameters

According to the current state of the technology, the PLF applies different sensor technologies and indicators being measured, which might be grouped into two major categories: (1) static, which uses some static infrastructure to measure different environmental parameters or herd / individual behavior using some cameras and (2) dynamic, which usually are attached to the individual animal or bird and uses some radio identification system like RFID (radio frequency identification) to bind data to a particular individual. Since the bird herd is very varying and the number of birds as stated earlier is relatively large the individual sensor systems are not further considered in our article.

The following table (Table1) summarizes the types of sensors used to monitor poultry welfare using static sensing approaches.

Table 1. Key sensor technologies and potential applications to improve poultry welfare [8], [9]

Sensor type		Application
Air quality Air temperature Air movement and speed Humidity Light intensity		Assessment of indoor climate conditions
		Broiler final weight forecast
Sounds	Broiler incubation	Monitoring hatching for better productivity
	Broilers	Feed intake measurements
		Growth forecasts
		Farm thermal comfort assessment
	Laying hens	Stress measurement caused by changing the temperature of the environment
		Determination of pecking of feathers
Movements		Insufficient movement detection
		Use of the geographic information system to assess the use of the room and the behavior of laying hens
		Chicken leaps between perches and their effects on the onset of bone fractures
General health indicators		Determination of avian influenza by estimating broiler temperature variation in a group of birds using a distant measuring system
		Detection of avian influenza by estimating broiler activity

The welfare and health of the broilers depend on the farm environment, which, in case of improper environmental control, may result in digestive, respiratory, and behavioral disturbances. Because of these disturbances, the productivity falls and the bird death ratio increases. Therefore, we see that such environmental indicators as temperature, relative humidity, vibration, NH and NH_3 concentration, and CO_2 concentration are important to be treated and controlled according to the recommendations. Unfortunately, our study revealed that PLF systems rarely provide the full stack approach from the sensors up to the decision support by appropriate IT solutions.

We assume that one of the main reasons why those solutions are still not largely used by PLF providers is the complexity of the recommended conditions, which depend on different production periods and even breeds. The summary of the recommended values of different environmental indicators is provided in Table 2.

Table 2. Recommended values of environmental indicators [10], [11], [12]

Sensor type	Recommended and critical values	
Air temperature	Period	Temperature
	Day 1	32–34 °C
	During Week 1	30 °C
	During Week 2	26 °C
	During Week 3	22 °C
	During Week 4	20 °C
Humidity	In the case of humidity, several measurements shall be distinguished – (1) absolute humidity – existing humidity in grams per 1 m^3 air; (2) maximum humidity: the maximum moisture content, which may be on 1 m^3 air at a specified temperature; (3) relative humidity – humidity ratio (maximum humidity to current humidity), expressed as a percentage.	Perfect level 50–60%. Impacts depend on temperature. Growth is adversely affected at > 29 °C and > 70% relative humidity.
Air composition and quality	Ammonia (NH_3)	Perfect level < 10 ppm. The odor concentration of 20 ppm and more can be determined. > 10 ppm kills the surface of the lungs. > 20 ppm may decrease growth rates depending on temperature and age.
	Carbon dioxide (CO_2)	Perfect level < 3000 ppm. > 3500 ppm causes ascites. High concentrations of carbon dioxide are fatal.
	Carbon monoxide (CO)	Ideal level < 10 ppm. > 50 ppm affects the health of birds. Carbon monoxide is fatal in high concentrations.
	Dust	It causes damage to the airways and increases susceptibility to diseases. The level of dust in the accommodation should be reduced to a minimum.
Air movement and speed	Air movement and speed	The recommended airspeed used in the farm shall be between 0.1 and 0.2 m/s. It can be different for different types of birds, at other temperatures and other ages of birds. At temperatures above 25–30 °C, air speeds exceeding 0.1–0.2 m/s will have a positive effect as such conditions help the animals to cool.
	Air pressure	The air pressure in the accommodation must ideally be not more than 42 Pa and not less than 37.5 Pa.
Venting rate	Weight of bird, kg	Minimum ventilation speed, m^3/h.
	0.05	0.08
	0.25	0.30
	0.50	0.51
	1.00	0.86
	1.50	1.17
	2.00	1.45
	3.00	1.96
	4.00	2.44

Climate control, lighting, and stocking density must be within acceptable limits. Deviations from these parameters may significantly impact animal welfare and farm sustainability. Jackman *et al*. [9] have developed a well-performing prediction model to calculate the final mean bird weight in broiler flocks, using sensors for temperature, relative humidity, CO_2, and ammonia concentrations. The model showed excellent accomodition-specific prediction ability ($r^2 = 0.89$) between the predicted and observed bird weight based on the conditions of the environment. From the study provided by [9], we see that not all of the environmental indicators are needed for relatively good predictions, and the initial data has an essential value for model training. Therefore a relatively simple continuous real-time environmental monitoring system could be used to provide a warning system for potential deviations from targeted weight gains and welfare risks.

3.2 Physiological Measurements and Reference Growth Schedule

A live forecasting model requires a large number of birds' weight input to be regularly estimated. During the rapid growth period (day 20 – day 40) the broilers can gain more than 100 grams per day, which defines a necessity to measure the body weight, ideally, every day to respond to unwanted effects and to collect data for further analysis or modeling (especially in the context of machine learning). Accurate information on live weight and coefficient of variation (V%) is essential to ensure that the maximum number of birds falls within the desired weight. Some of the recent studies ([11] and [13]) allow to assess the weight growth dynamics (see Figure 3) and potential uniformity within the herd (Table 3).

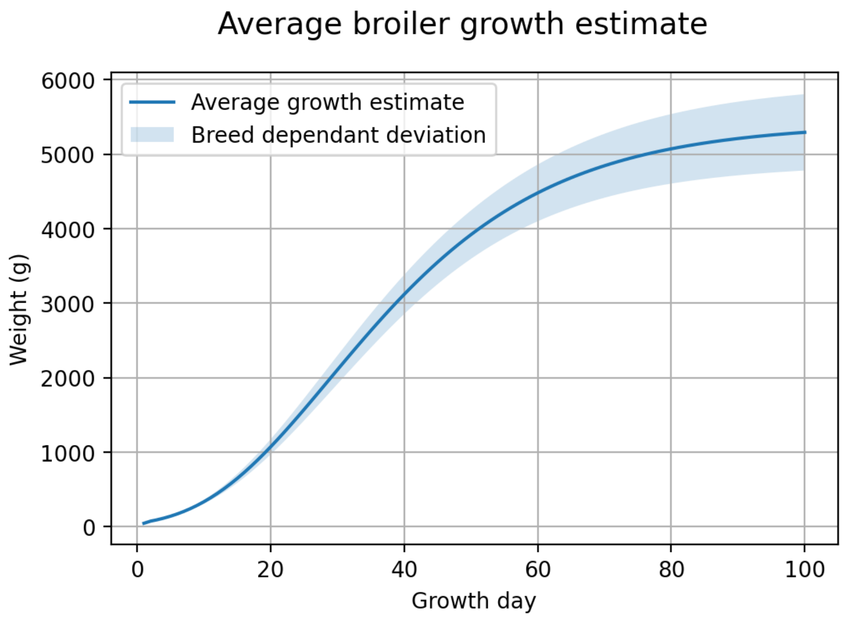


Figure 3. Broiler average growth estimate per day in grams [13]

According to [11], measured by the coefficient of variation (the standard deviation/average body weight multiplied by 100), the greater the number, the more variable the weight of the herd body. The assessment of live weight is within +/– 2% of actual live weight and is correct in 95% of cases.

Table 3 Minimum number of birds for accurate assessment of live weight and herd uniformity [11]

Uniformity of herd	Number of birds to be weighed
Uniform (coefficient of variation = 8%)	61
Medium uniform (coefficient of variation = 10%)	96
Poorly uniform (coefficient of variation = 12%)	138

When weighing birds manually, they must be considered regularly and at the same time and selected from different places in the barn.

A study in 50 poultry farms reported by [10] shows that the maximum weight of the bird is reached in 8 to 9 weeks. Still, at the same time, it is recognized that the ideal weight of broilers is approximately 2000 g and can be achieved within 5 to 6 weeks (about 40 days), with an average of 1100 g of feed per week. It has also been found that in holdings that do not use PLF technologies, such weight broilers typically reach 6 to 7 weeks and a slower weight gain at a similar or higher amount of feed consumed.

Unfortunately, the most widespread broiler's body weight estimation method is manual measurement, which requires a lot of effort and suffers from the "human factor" resulting in weak precision and low frequency (once per week) of the measurements. This limits the use of the collected data in combination with the environmental sensor data, which are collected with a much higher frequency. Therefore, we see a necessity to build a model that allows fitting low frequency manually collected data to perform both interpolations for data augmentation and extrapolation for prediction. The following section discusses the developed model.

4 Sample Data Set and Its Augmentation Model

To collect the initial data, we have developed a data acquisition system, that collects both manual and sensor data. While the sensor data has the same sensors as suggested by studies in [9], body weight data are collected manually once per week in each accommodation (barn). Having the data sample, it is possible to observe that the weight dynamics of the birds correspond to the results of other reported research and do not follow a linear trend (see Figure 4).

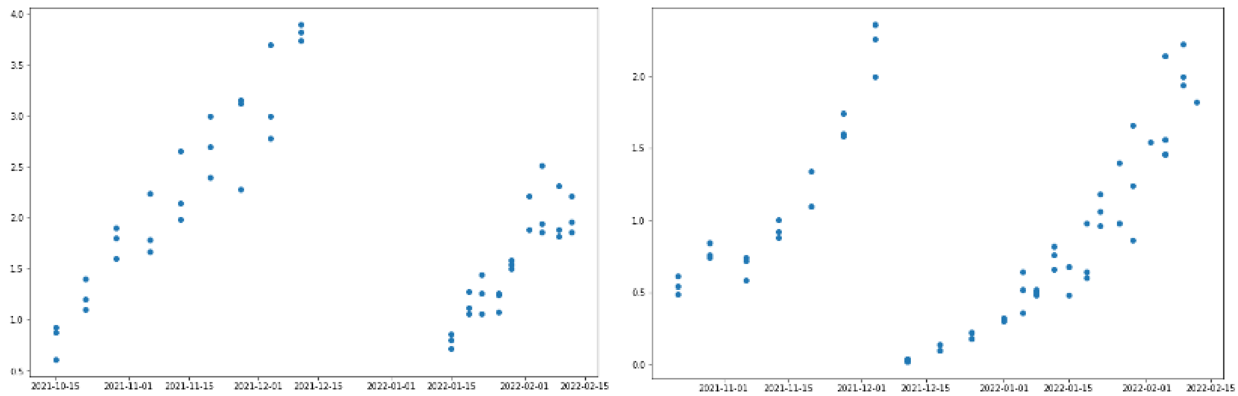
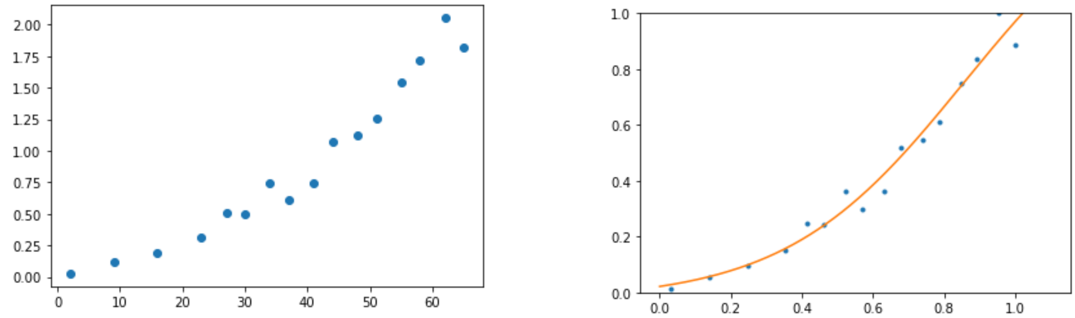


Figure 4. Broiler growth estimate in two separate barns for two production cycles (horizontal axis – date of measurement taken, vertical axis – broiler weight in kg)

Depending on the barn, in Figure 4, dynamics are a little different, but, in general, they reach the same weight values and follow the growth speed. However, the number of data points is too small to provide solid ground for reliable training of forecasting models. Since the weight are registered for different birds, which provides deviating values, the average weight values for each measurement act is even approximate, allowing the use of basic regression (see Figure 5).



A – initial averages measurements B – logistic regression model

Figure 5. Broiler growth modeled using different models in barn 2

It is of great importance for the farm to cut the production at its maximum value and reliably plan the production using an appropriate forecast. It can be noticed that Figure 5-B, corresponds to the sigmoidal trend of the studies presented in Figure 3 for the first weeks of the growth.

However, the logistic model loses its accuracy for more extended periods. Therefore, we identified a necessity to acquire a more accurate model that corresponds to the dynamics of the whole production cycle by extending on studies presented in [11], [13], [14] through the parameterized model, where parameter values are acquired by optimization. In [14], the following model is provided:

$$Wt = Wo\exp((\tfrac{L}{K})(1 - \exp(-Kt))), \quad (1)$$

where
- Wt – weight at time instant t;
- Wo – initial weight;
- K – weight growth constant;
- L – a specific growth ratio at the modeling start time instant $t = 0$.

In (1), the optimized parameters are K and L, and the optimization task definition is defined in (2):

$$min[e(x, K, L)] \text{ – according to parameters } K \text{ and } L, \quad (2)$$

On a fixed time scale $x = \{x_1, x_2, \cdots, x_n\}$, where

$$[e(x, K, L)] = \frac{1}{n}\sum_{i=1}^{n}(f(K, L, x_i) - g(x_i))^2,$$

where
- x_i – time instants of the measurements;
- $g(x)$ – weight measurements;
- $f(K,L,x)$ – model from (1) for time instants x;
- $e(x)$ – MSE (mean squared error) between measurements and modeled values;
- K – weight growth constant;
- L – a specific growth ratio at the modeling start time instant $t = 0$.

Using the genetic optimization approach [15] helps avoiding local extreme traps and allows finding near-optimum solutions. The acquired model allows modeling weight values for every production day, thus augmenting the dataset and enabling the use of the forecast model, which depends on several samples, as shown in Figure 6.

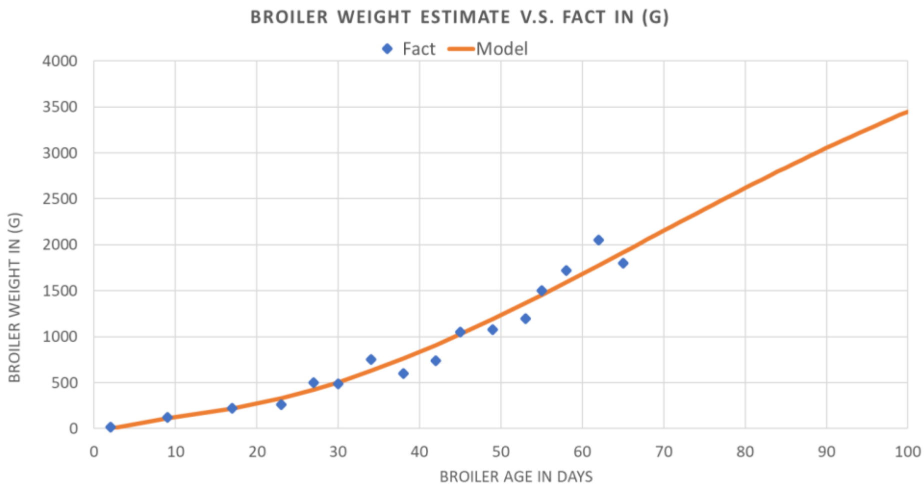


Figure 6. Broiler weight model vs. factual measurements in barn 2

The model can be used to prepare sample data for further analysis or forecast model training while providing data augmentation capabilities by complementing the measured data points with modeled points. The same approach was applied to other barns to ensure its correspondence to the overall production cycle and weight gain dynamics provided by [13].

5 PLF Decision Support System Design

Having the sensor infrastructure and the model that allows augmenting the manually measured data, it is possible to design an IT solution that supports the decisions based on the production results – broiler weight forecast. A software system's prototype has been developed for data processing that employs the power of docker infrastructure for containerized models exposed as services to the business systems. Its architecture is presented in Figure 7.

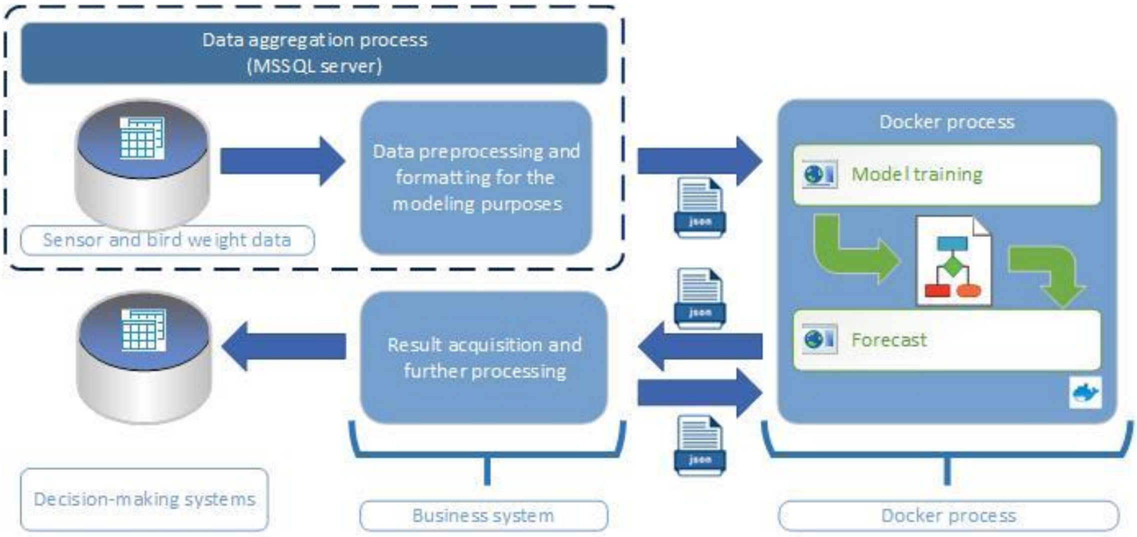


Figure 7. The architecture of the data processing software system

The initial data collected from manual operations and sensors are stored in a dedicated database, which enables to run data preprocessing algorithms for data formatting. The formatted data is passed to the containerized model, which employs the presented data augmentation approach to enrich available information for forecast model training (the forecast model is not discussed in this article), and the model calls for forecast requests. The operation steps are summarized in Figure 8.

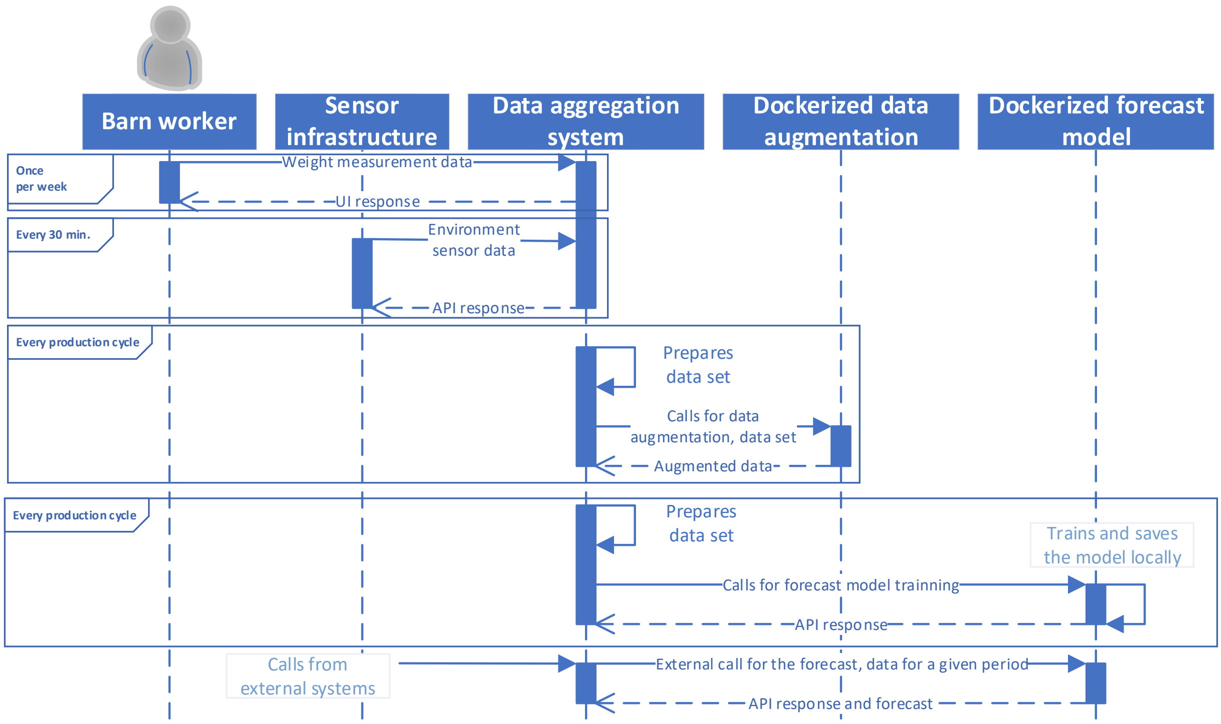


Figure 8. Main steps of the data processing

Since the model is exposed through the docker container as a web service, it is relatively straightforward to implement model training and call scenarios for different barns and production cycles, addressing scalability and multi-tenancy if needed. In Figure 8, the external system is any business or decision support system that uses the developed data processing system for forecast acquisition.

As can be noticed, both the data augmentation and forecast model training are done every production cycle for a barn to keep the forecast model up-to-date reflecting the current production process by fitting the recent data on top of the historical data. The particular period and data formats are not discussed here since the forecast model is out of the scope of this article.

6 Conclusions

The reported study summarizes recent trends in the poultry industry and provides an insight into the weight forecast problem, which is the central concern for successful production management and forecast model training due to low frequency and low accuracy data in the loop. The identified research questions guided the development of the PLF IT support model for poultry production. Section 2 addressed the focus of previous research in PLF (RQ1), subsection 3.1 investigated the key environmental parameters in the poultry industry (RQ2) while subsection 3.2 and Section 4 were devoted to modeling broiler growth (RQ3). Consequently, we propose the data processing pipeline for poultry production.

One of the problems in the poultry industry is manually collectable data, e.g., bird's weight, which causes inconsistency with the frequency of automatically collected sensor data. We conquer this problem with a practical approach to augment manually acquired data with a model, which is parametrized by using genetic optimization for the best fit. After the model is acquired, it is relatively simple to augment manual measurements with modeled data, which is an essential step to prepare datasets for forecast model training and use.

The proposed software system architecture along with chosen weight prediction model serves as a ground for the IT system's implementation. In the current research, the prototype of the system is implemented and used for experiments with gathered data. Additional questions to be addressed relate to the choice of a particular forecast model which can be decided upon in further development steps. Since the proposed architecture is relatively simple and independent from models used for the forecast (they are encapsulated into a container), the proposed approach enables further development of practical software systems and services applicable in the poultry industry at a scale as well as combining different models for different breeds, production processes or clients.

The validity of this research is partly limited to the acquired data from a particular poultry farm and the acquisition of environmental factors. Limited data sources might affect generalization capacity. Nevertheless, the study is based on previous scientific research and the collected results conform with broiler growth trends reported in the literature.

Our next research steps include (1) addressing broiler weight forecast as a time-series modeling, (2) implementing the proposed IT solution and (3) evaluating the effect of change in environmental factors, e.g., the temperature in the barn, on the broiler growth.

Acknowledgements

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