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Reliable use of smart cameras for monitoring biometric parameters in buffalo precision livestock farming

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ABSTRACT
Precision Livestock Farming, as a specific sub-sector of Public Health Informatics, focuses on the application of process engineering principles and techniques to achieve an automatic monitoring, modelling, and management of animal productions. In the present work a timely "protocol" is proposed for unobtrusive direct/indirect monitoring of biometric parameters for the estimation of body conditions on Mediterranean Buffalo populations, using low-cost automated systems already present on the market i.e., smart cameras endowed with depth perception capabilities.

Section: RESEARCH PAPER

Keywords: Public Health Informatics; precision livestock farming; measurement; mediterranean buffalo; smart cameras; 3D/2D image analysis

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1. INTRODUCTION

As widely reported in the literature, the Public Health (PH) sector encompasses several important disciplines, such as epidemiology, biostatistics, and environmental science. Among the latest and most critical progresses registered in PH, (i) One Health is a transdisciplinary approach that recognizes the connection between people's health, animal health, and the surrounding environment, while (ii) Public Health 3.0 addresses the collaboration necessary to achieve that integration [1].

In the wake of this, the "systematic application of information and computer science and technology to PH practice, research, and learning" [2] is referred to as Public Health Informatics (PHI), which stands among the sub-areas of the overarching BioMedical and Health Informatics (BMHI) field [3]. In this scenario, as concerns globally raise especially about environmental sustainability and animal welfare, Precision Livestock Farming (PLF) is reported as a declination of PHI focused on the application of process engineering principles and techniques to livestock farming, in order to an automatic monitoring, modelling, and management of animal production.

PLF's primary goal is to make livestock farming more economically, socially, and environmentally sustainable, thus pursuing surveillance, reporting, and health promotion goals [4], [5]. Awareness is therefore rising worldwide as to the importance of a systematic deployment, by means of smart computing and sensing technologies, of integrated (and economically sustainable) solutions for continuous monitoring of quality and salubrity of the production environments. The scope is to achieve an integrated vision between production characteristics, animal welfare, and security issues. In particular, the adoption of new types of approaches for weight assessment aims to increase the accuracy of measurement and, accordingly, to improve the monitoring of animal performance, thus potentially providing major benefits to both the herdsmen and the animals in their care [6]-[8].

About one ninth of the global cattle population is composed by an essential domestic bovid, the so-called water (or river) buffalo (*Bubalus bubalis*), also known as Asian buffalo. The 3% of such population is represented by the Mediterranean buffalo. In 2001 the Italian Ministry of Agriculture and Forestry, thanks to long isolation and lack of crossbreeding with other strains, further recognized the "Mediterranean Italian buffalo" breed [9]. In South Italy the whole Buffalo–related dairy production and supply chain represents a leading sector of the entire Agri–food arena. Although understudied if compared with other cattle breeds, the information on body weight prediction in Mediterranean buffaloes is of great importance for making much better decisions as to breed standards, breeding schemes, flock management, and conserving gene reserves [10], [11].

The present study aims therefore to propose, formalize and test a "protocol" for unobtrusive direct/indirect monitoring of biometric parameters for the estimation of body conditions on Mediterranean Buffalo populations, using low-cost automated systems already present on the market i.e., smart cameras endowed with depth perception capabilities. In particular, a set of Machine Learning–based algorithms (linear regressions; neural networks) were deployed on the set of measurements obtained by a combination of three different devices – a photocamera, a Depth Camera, and a LiDAR Camera – compared with traditionally hand-performed measurements on Mediterranean Buffalo calves from the birth to their complete weaning. The goal is twofold: (i) Figure out the most timely measurement tools to be used to correctly estimate and predict the weight trajectories; and (ii) verify whether the adoption of an electronic measurement system can lead to best practices in Precision Livestock Breeding.

The paper is organized as follows: after the introduction, a brief view is provided as to cattle monitoring systems, and the many phases of the experimental design are reported; results are therefore described, and some discussion and conclusions are eventually indicated.

2. STATE OF THE ART

2.1. (Technology–enabled) cattle monitoring systems

Calves rearing, especially during the first period of life, is one of the most delicate phases of the entire production process in a dairy farm, for both bovine and buffalo species. Inadequate nutrition or unhealthy environmental conditions may affect calves' growth and, more in general, their correct development in terms of both morphological and productive performances. Currently, an increasing branch of the computer science and metrology literature is dealing with the automatic measurement of morphological features in cattle via 2D and 3D vision-based techniques to predict their live weight using machine learning– and deep learning–based approaches, thus overcoming all the intrinsic limitations of conventional manual scoring techniques e.g., labour intensive, highly subjective, results often inaccurate and inconsistent [12]-[14].

Among the most recent works concerning dairy cows, a 3D full-body scanning device was used by [15] for monitoring morphology and growth, as well as to estimate indicators such as body volume, surface area and body weight. Measured weights were then compared with those predicted from regression models based on volume, area or morphological traits determined from 3D images. 3-dimensional cameras positioned to view the cow from the top, right side, and rear were used by [16] to implement an automated BCS classification. Further, an automatic visual detection and biometric identification of individual Holstein-Friesians via convolutional neural networks (CNNs) and deep metric learning techniques was discussed by [17], while [18] deployed a Mask-RCNN segmentation algorithm to segment the images of heifers, as input to a CNN model developed on the Keras platform to predict their body mass. A 3D surface reconstruction and body size measurement system based on multi-view RGB-D cameras was instead developed by [19] using Kinect depth cameras to obtain the point clouds of freely walking pigs from three different views (i.e., upper view, left-view and right-view).

3. PAPER CONTRIBUTION

3.1. Experimental design

The trial lasted 90 days (13 weeks, from T00 to T13) and was carried out in the period June-September 2022 in an Italian Mediterranean buffalo farm, located in Serre (province of Salerno, Campania Region). A longitudinal observational study was conducted on 30 female buffalo calves, from their birth up to the weaning phase [20]. To predict body weight, for each of them every week the following three biometric measurements were taken, according to the methods suggested by e.g., [21] (see Figure 1):

- height at the withers (WH): vertical distance between the withers (highest point of the back, between the neck and shoulder blades) and the ground;
- body length (BL): oblique distance between the tip of the buttock (apophysis of the ischium) and the tip of the shoulder (shoulder joint);
- chest girth (CG): minimum value measured just behind the shoulders.

Manual measures were performed using a wooden tape for WH, and a roll tape for BL and CG. Two Intel ® RealSense™ cameras (D415 Depth camera, and L515 LiDAR camera) along with a RICOH ® WG–60 photo camera, were used for measuring WH and BL – in this first set up of the observational study, CG measures could only be made with the photo camera, and manually.

To perform as many noiseless measures as possible, the calves were entered in a containing structure specifically created to keep them stationary. The tip of the shoulder, the apophysis of the ischium, and the withers were coloured using a white spray, to rely on reference points for the image analysis phase, because of the black colour of the buffalo mantle. The containing structure was built considering, besides the availability of spaces, the possibility to take photos and make video recordings while minimizing the incidence of natural light as source of noise for the image analysis process.

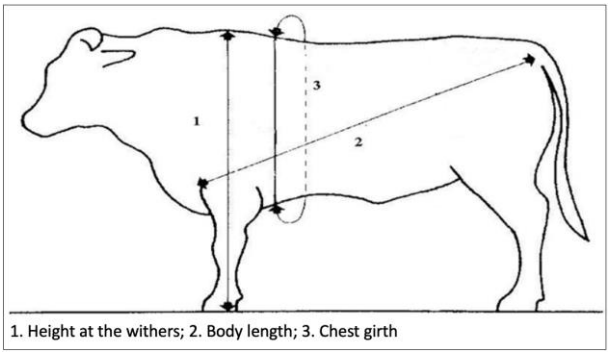

Figure 1. In vivo body measurement for Mediterranean Buffalo calves.

3.2. Smart cameras setup

To use the RICOH photo camera in an as steady and effective as possible way, it was placed at a fixed distance (about 5 m) from the animal, resting on a photographic tripod. Such distance resulted as the optimal compromise between a number of factors: on the one hand, it was necessary to reduce the impact of sunlight; on the other hand, the camera needed to be levelled before taking the photographs, so to match the degree of inclination of the platform the calves rested upon (on the vertical and horizontal planes, and the 45° angle), with the same inclination degree as the camera; the "x2" zoom factor was set.

The "ImageJ" open–source software was then used for processing the analysis of the 2D images taken to obtain the measures for WH, BL, and CG (Figure 2). For what concerns the D415 Depth Camera and the L515 LiDAR camera, the features of Intel RealSense technology related to sensing and depth perception capabilities, were exploited. Since RealSense products are supported by a specific Software Development Kit (SDK) and a cross-platform library for third-party software developers, a script was developed to make the measurements using the cameras' hardware.

The software used for the script, including the one to build the libraries, were Visual Studio 2019 and CMake. The main libraries used were instead the Intel library "librealsense2.lib" and the OpenGL library "glfw3.lib". The main structure of the script is divided into a video processing thread, and a rendering thread. The former retrieves data from the camera in use and provides the data to the latter.

The cameras were adhered to a laptop via strips of adhesive Velcro, and then connected to it with a USB cable, to make possible for the operator to make an as effective as possible video recording surrounding the animal examined. To record the entire body of the single calf, (i) the L500 depth sensor and the RGB camera were activated for the L515 LiDAR Camera (Figure 3), and (ii) the stereo module and the RGB camera were activated for the D415 Depth Camera (Figure 4).

Once made the recordings, the "IntelRealSense Viewer" program was used to model the 3D image, and then carry out the measures for WH and BL.

3.3. Data analysis

Three different models – that is Multiple Linear and Polynomial Regression (MLR/MPR), and Artificial Neural Network (ANN) – were implemented (and compared) to predict the progression of calves' body weight during the trial, starting from the body measurements taken. R Studio and Excel Statistical software were used for the analysis.

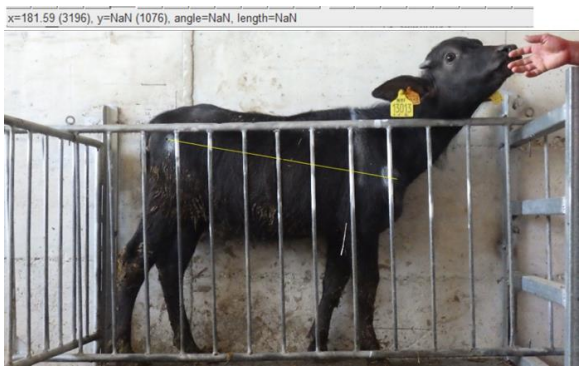

Figure 2. Example of measure of BL using ImageJ from a picture taken with the RICOH photo camera. The animal is in a containing structure, and the white dots are made to make the measures possible.

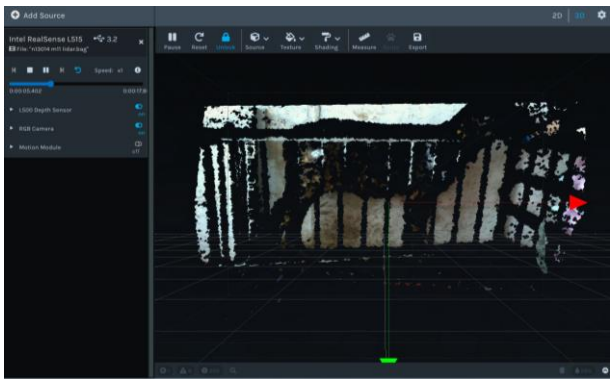

Figure 3. Example of recording via L515 LiDAR Camera.

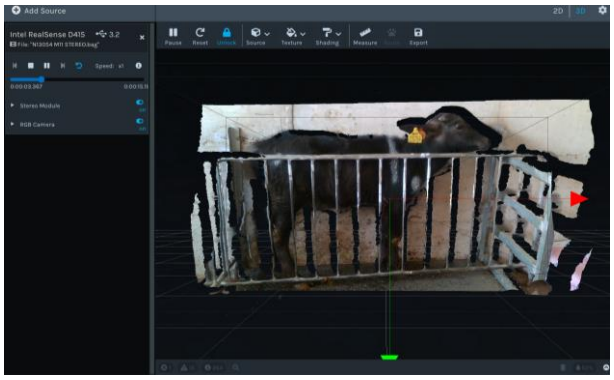

Figure 4. Example of recording via D415 Depth Camera.

The general model of MLR uses the following equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon\,. \quad (1)$$

A quadratic model was chosen to implement MPR, to prevent conditions of data overfitting, as reported in the following equation:

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \varepsilon\,. \quad (2)$$

In both cases are: y = variable value; β_0 = intercept; β_k = k-th–regression coefficient; ε = standard estimation error.

For what concerns the neural network, a perceptron multilayer network with backpropagation was used. The ANN consisted of input, one hidden and one output layers. The number of nodes of the input layer corresponds to the number of variables describing the calves' body features tested; the number of neurones in the output layer equals the number of classes (that is the number of calves involved in the study).

To evaluate the reliability of the measurements systems deployed, that is in other words to formalize and test the reliability of the "smart cameras–based monitoring protocol", the following goodness-of-fit criteria were used [22]:

- Relative Error (*RE*) between the (manual) benchmark measure and the one obtained with each of the three cameras:

$$RE = \left| \frac{\overline{manual}\ value - \overline{camera}\ value}{\overline{manual}\ value} \right|$$

- Standard Error (*SE*):

$$SE = \frac{standard\ deviation\ of\ the\ sample}{\sqrt{population\ size}} = \frac{\sigma}{\sqrt{n}}.$$

- Mean Squared Error (MSE):

$$MSE = \frac{\sum_{i=1}^{n} SE_i}{n-2}$$

- Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n-2}\sum_{i=1}^{n} SE_i},$$

where: n is the size of the dataset; SE_i is the difference between the i-th 'manual' value and the corresponding i-th 'camera' value, for each of the three cameras used. The use of the quantity $(n-2)$ for *MSE* and *RMSE* is aimed at improving the accuracy of the results.

4. RESULTS

During the trial it was only possible to make 2195 single evaluations of WH, BL, CG, and body weight, equal to ≈ 90 % out of the total of 2430 possible measurements (obtained by multiplying the total foreseen measurement per each week, for the number of weeks of the trial). The difficulty was mainly due to either technical problems (excessive noise during the image analysis, caused by the sunlight), or to the impossibility to keep the animal stable in the containing structure.

4.1. Descriptive statistics

Table 1 summarizes the descriptive statistics of response and explanatory variables for the Mediterranean buffalo calves involved in the study, according to the measures performed (both manually and with the three cameras), reported as Mean ± Standard Error. To compare the effects of the different types of measures, the two-sample Student's T test was performed.

Table 2 shows further the Pearson's correlation coefficients for determining the relationship between BW and body measurements. Some quite significant correlations are found with WH RICOH (0.777), WH D415 (0.844), WH L515 (0.878), BL RICOH (0.853), BL D415 (0.895) and BL L515 (0.907), respectively ($p < 0.01$).

4.2. Model comparison

MSE, *RMSE*, and Pearson's R^2 goodness-of-fit criteria were used to evaluate the performance of the model. In particular, the model performances were evaluated according to the lowest MSE and RMSE values, and the highest R^2 value [23], [24]. Figure 5 and Figure 6 show *MSE* and *RMSE* trends for WH and BL, respectively – as the only body features, unlike CG, for which it was possible to take measures with the three cameras set.

In particular, for what concerns WH the lowest values for both *MSE* and *RMSE* appear to be those related to L515 (AVG_{MSE} = 11.41; AVG_{RMSE} = 3.02). The result is only apparently better in this case too, given the smaller number of measurements taken with this tool, thus returning more reliable values than those from D415 (AVG_{MSE} = 15.03; AVG_{RMSE} = 3.72). BL shows instead an overall better trend of D415 (AVG_{MSE} = 29.78; AVG_{RMSE} = 4.99).

Figure 7 shows an overall comparison of the BW prediction models starting from WH, BL, and CG. The columns refer to the measurement modes (manuale/manual, camera/L515, and dstereo/D415); the rows to the type of model used (lm: MLR; poly: MPR; nn: ANN). In each of the nine panels, the *x*-axis reports the actual value of the weight; the value estimated from the corresponding model is reported on the *y*-axis. The closer the

Table 1. Descriptive statistics.

Var.	Manual	RICOH	D415	L515	Manual/RICOH	Manual/D415	Manual/L515
	Mean ± Std. Error	*Mean ± Std. Error*	*Mean ± Std. Error*	*Mean ± Std. Error*			
WH	86.18 ± 1.13	89.75 ± 1.33	84.81 ± 1.32	83.81 ± 1.19	0.05	0.03	0.07
BL	74.04 ± 1.54	78.33 ± 2.06	71.30 ± 1.75	69.01 ± 1.68	0.03	0.02	0.07

Table 2. Correlation Matrix.

	WH Man	WH RICOH	WH D415	WH L515	BL Man	BL RICOH	BL D415	BL L515	CG Man	BW
BW										1.00
CG Man									1.00	0.92
BL L515								1.00	0.88	0.91
BL D415							1.00	0.95	0.86	0.90
BL RICOH						1.00	0.89	0.90	0.84	0.85
BL Man					1.00	0.86	0.90	0.92	0.81	0.90
WH L515				1.00	0.86	0.84	0.86	0.85	0.82	0.88
WH D415			1.00	0.83	0.81	0.80	0.81	0.83	0.82	0.84
WH RICOH		1.00	0.74	0.81	0.77	0.88	0.77	0.76	0.74	0.78
WH Man	1.00	0.86	0.90	0.92	0.87	0.87	0.90	0.90	0.90	0.91

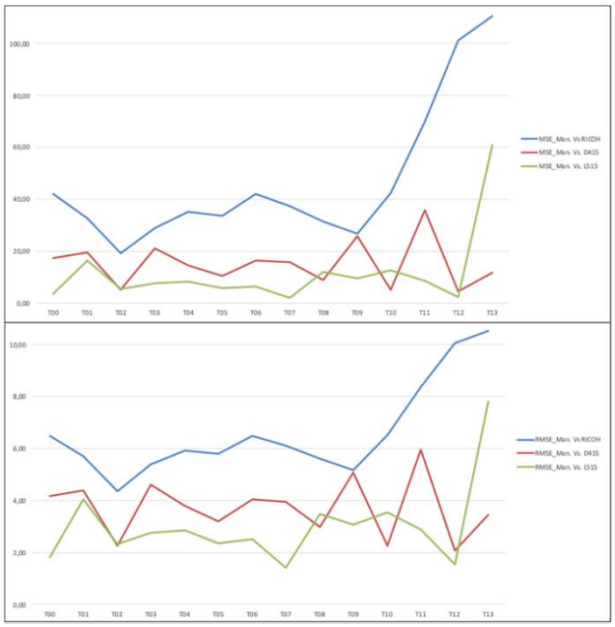

Figure 5. MSE (upper) and RMSE (lower) trends for WH.

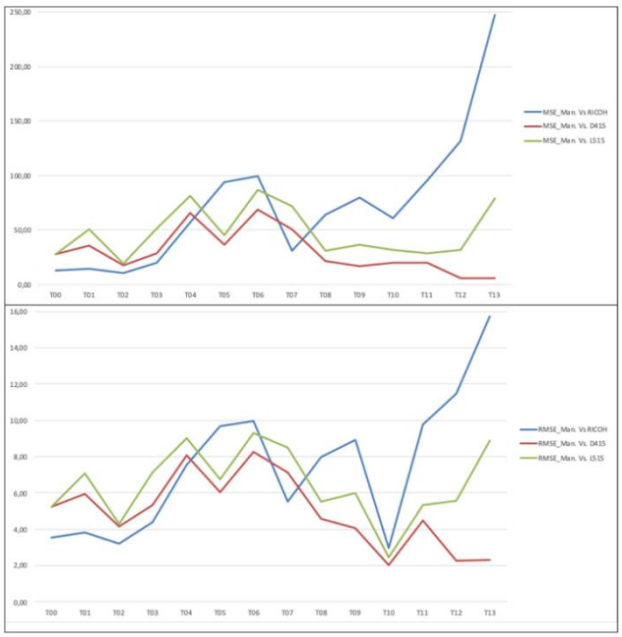

Figure 6. MSE (upper) and RMSE (lower) trends for BL.

points are to the bisector, the better the prediction obtained. All the models perform reasonably well: in the linear model the correlation loses some effectiveness at the top of the distribution, likely because of the heavier calves; comparable results are inferred instead for the other two models.

Table 3 shows Pearson's R and R^2 values for each of the models: the closer the value is to 1, the better the prediction provided. Besides the manual measurements, the best prediction is the one performed by means of ANN, starting from the measurements taken with the Stereo camera D415.

Table 3. Pearson's R^2 Goodness-of-Fit.

Model	Pearson's R	Pearson's R^2
manuale_poly	0.962	0.925
manuale_nn	0.961	0.924
dstereo_nn	0.961	0.924
manuale_lm	0.958	0.918
dstereo_poly	0.954	0.910
dstereo_lm	0.950	0.903
camera_nn	0.943	0.889
camera_poly	0.942	0.887
camera_lm	0.935	0.874

5. DISCUSSION AND CONCLUSIONS

Setting up an automated (and contactless) method to perform body measurements, and predict the progression of body weight, is a long-desired application for the animal production systems.

The results of the longitudinal observational study described in the paper witness about the reliability of using low-cost smart cameras for unobtrusive direct/indirect monitoring of biometric parameters for the estimation of body conditions on Mediterranean Buffalo populations – the average cost for a stereo camera and a photo camera, is about 230 Euros, and the average cost of a LiDAR camera is about 520 Euros. More specifically, the best overall performances were obtained with D415 Depth camera. A similar score was observed for L515 LiDAR camera too, although a lesser number of measurements were taken, due to the two main limitation factors that affected the experiment, that is: (i) continuous movements of the animals, that resulted in a poor vision of the reference point on the calves' body (drawn with the white spray), and therefore in the impossibility of pointing the mouse on them during the image processing phase; and (ii) good functioning of L515 camera compromised in situations of strong light, which again made it

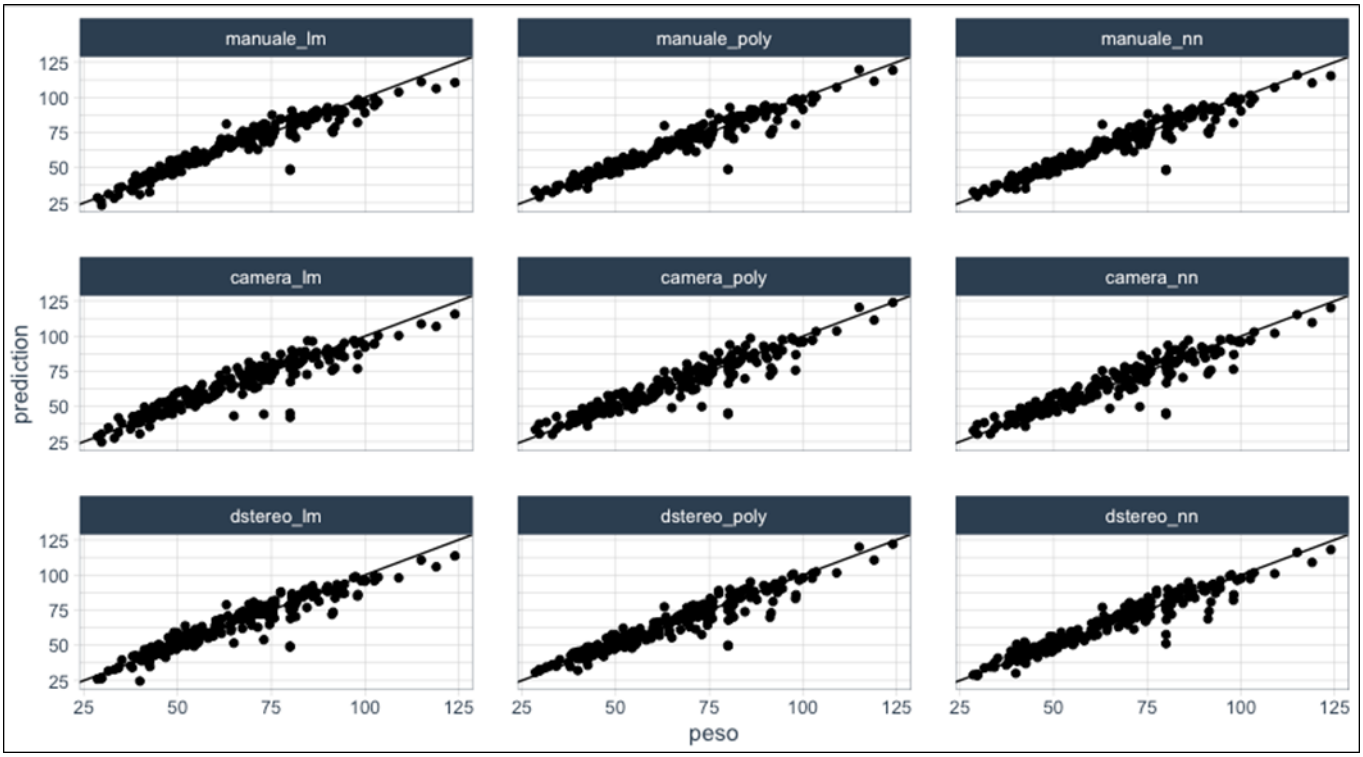

Figure 7. BW prediction using MLR (lm, left column), MPR (poly, center), and ANN (nn, right column).

quite difficult the identification on the video of the reference points. Further, the use of the photo camera provided a valid support because, although of course shooting 2D pics, resulted the least affected from the mentioned limitation factors. Rooms for improvement are anyway possible to overcome the experienced issues, which will be tackled in future steps of this line of research.

The experience conducted shows that, while on the one hand animal health (to which dairy farming broadly relates) is playing a critical role as to the general re-thinking of Public Health [25], on the other hand the continuous improving of the Smart Farming sector, also through the digitalization of livestock farming activies, is meant to widen Public Health Informatics policies and strategies [1], [3]. Also worth mentioning, under an epidemiological point of view, that initiatives are being conducted in PLF focused on the use of smart cameras for detecting specific health conditions (see e.g. [26]).

Accordingly, the "P" for Public in PHI is called to also comprise the concepts of: (i) Precision – improvement of the whole Farming Data Management set, and to figure out accordingly "data–driven"–like business models [6]; Personalized – the 'per animal approach', as the timely management of the smallest manageable production unit's temporal variability [27]; and Predictive – use of AI-related techniques on animal data, to improve human quality of life [28].

An effective monitoring of dairy cattle can positively affect (i) human health, thanks to a better supply chain control [29]), and (ii) environmental health, as pairing weight control with nutrition management can lead to an improvement of animals' eating habits, to reduce their emissions of Green House Gases (GHG) [30] – in this regard, Kumari's approach that employs a system dynamic model to link the estimation of methane emissions to different types of consequences, is of particular interest [31]. More in general, initiatives like the one descripted in the present work can address human, animal, and environmental systems' needs and challenges, collecting data and selecting timely metrics to assess expected/unexpected outcomes and effects, thus perfectly matching with the One (Digital) Health framework requirements and proposals [32]-[34].

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