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Animal biometric assessment using non-invasive computer vision and machine learning are good predictors of dairy cows age and welfare: The future of automated veterinary support systems

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ABSTRACT

Digitally extracted biometrics from visible videos of farm animals could be used to automatically assess animal welfare, contributing to the future of automated veterinary support systems. This study proposed using non-invasive video acquisition and biometric analysis of dairy cows in a robotic dairy farm (RDF) located at the Dookie campus, The University of Melbourne, Australia. Data extracted from dairy cows were used to develop two machine learning models: a biometrics regression model (Model 1) targeting (i) somatic cell count, (ii) weight, (iii) rumination, and (iv) feed intake and a classification model (Model 2) mapping features from dairy cow's face to predict animal age. Results showed that Model 1 achieved a high correlation coefficient ($R = 0.96$), slope ($b = 0.96$), and performance, and Model 2 had high accuracy (98%), low error (2%), and high performance without signs of under or overfitting. Models developed in this study can be used in parallel with other models to assess milk productivity, quality traits, and welfare for RDF and conventional dairy farms.

1. Introduction

Efficient animal welfare assessment is critical for the agricultural industries and the continuous food production, maintenance of food quality traits, and ultimate food security [1]. Significant advances have been made in the automation of animal-based food production, such as robotic dairy farms (RDF) [2–4]. However, many RDFs still rely on veterinarians for welfare assessment and treatment of illness or complications related to production, such as mastitis [5–7], and other diseases detected using proxy measures, such as animal feed intake, weight, body temperature, and rumination activity [8–10].

Recent advancements in digital tools to assess biometrics and physiological parameters from farm animals have allowed monitoring the animals using short range remote sensing and non-invasive technologies, such as visible video (VisV) and infrared thermal imagery (IRTI) [11]. Our research group has recently published a complete review of these technologies for farm animals such as cattle, dairy cows, pigs, and sheep. Specifically, successful applications of digital tools to assess animal biometrics have been made to assess the early detection of respiratory diseases in pigs and biometrics for sheep, dairy cows, and cattle [11]. These advances can automatically generate monitoring parameters such as heart rate (HR), respiration rate (RR), and skin/eye temperature readings more efficiently and without imposing additional stress on animals from direct contact sensors [12]. However, they still rely on the interpretation of professional veterinarian personnel for welfare assessment or detection of illnesses based on more invasive tools, such as handling animals and blood work, among others.

Some important wellbeing parameters to monitor in dairy cows assessed in this paper are somatic cell count (SCC), animal weight, rumination, and feed intake. The SCC is an indicator of milk quality as well as a sign of udder infection known as mastitis [13]. Animal weight is important as an indicator of health, welfare, and milk production [14]. On the other hand, rumination is the process of regurgitating the feed, followed by remastication to break down the particles to swallow and pass through the reticulo-omasal orifice; this allows the enhancement of fiber digestion [15,16]. In the present study, feed intake refers to the

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amount of feed the cow consumed from the total provided by the robotic milker. This may be affected by several factors, such as stress; therefore, it is variable and quantified by the robot.

Previously, artificial intelligence (AI) methods based on automated computer vision algorithms for animal recognition and automated extraction of features have been used to develop machine learning (ML) models targeting indirect milk production and quality traits [12]. Furthermore, this is the first research to derive skin/eye temperature of farm animals using VisV only without requiring IRTI, which still can be cost-prohibitive compared to normal RGB cameras and cumbersome for data extraction, processing, and automated interpretation.

Following the latest advances in AI using VisV to assess fam animal biometrics, this paper proposed advanced modeling techniques based on ML using biometrics as inputs to target complex data such as SCC, animal weight, rumination, and feed intake (Model 1) and using feature extraction (using deep learning) from animal faces as inputs to target cow age as a target using classification ML modeling strategies (Model 2). Advances shown in this paper may improve the automation of RDF to assess not only milk productivity and quality traits [12] but also animal welfare and early detection of illnesses, such as mastitis.

2. Materials and methods

2.1. Animals, site, and ethics details

The study was conducted at the robotic dairy facilities located at the Dookie College, The University of Melbourne (UoM), Victoria, Australia (36°38′ S, 145°71' E). A total of 102 Holstein-Friesian cows were analyzed with one to five replicates per cow, with 282 observations. The Animal Ethics Committee of The University of Melbourne approved all protocols (Ethics ID: 2021-21466-18833-5). The robotic facilities consist of three Lely Astronaut milking units (Lely Holding S.à.r.l., Maassluis, The Netherlands) with a capacity for up to 180 cows per day. Cows wear a transponder neck collar (Lely Holding S.à.r.l., Maassluis, The Netherlands) for identification, registering their information, activity, and production data [12].

2.2. Video recording and analysis

Data were collected on 14–15th July and 4–5th August 2021 from 9 a.m. to 4 p.m. Cows that voluntarily approached the facilities for milking were directed to the crush for video recording either before or after milking to avoid bias and stress due to the milking effect. A 1 min VisV was recorded per cow each day using a FLIR DUO PRO (Teledyne FLIR LLC, Wilsonville, OR., USA), which can capture visible red, green, and blue (RGB) and infrared thermal videos (IRTV) simultaneously. However, for this study, only the VisV was used.

All VisV were analyzed using computer vision algorithms developed in Matlab® R2021a (Mathworks, Inc., Natick, MA, USA) by the Digital, Agriculture, Food and Wine group (DAFW) from UoM to assess HR and RR [12,17–19]. The region of interest (ROI) used for HR analysis was the eye section, while the nose was used for RR; these were labeled, automatically tracked, and cropped to further analyze these biometrics (Fig. 1). As detailed by Fuentes et al. [12], these algorithms work by analyzing the luminosity (L* value) changes on the green channel from the RGB color scale for HR and green to red (a*) color channel from CIELab scale for RR, using the photoplethysmography (PPG) principle. The HR outputs are obtained in beats per minute (BPM), while RR is in breaths per minute (BrPM). The video processing performance is dependent on the computer and processor used for the analysis. Using a gaming computer Alienware® (DELL, Round Rock, TX, USA) with 32 GB and 10 cores with parallel pool, the analysis per video takes 40 s with 7% central processing unit (CPU) usage and computer temperature range (27–33 °C) in individual cores.

The VisV were also labeled to detect and track the face of the cows using the Video Labeler application based on the point tracker Kanade-Lucas-Tomasi (KLT) algorithm in Matlab® Computer Vision Toolbox 10.0 (Mathworks Inc., Natick, MA, USA). These labels were analyzed for abrupt movements using a computer vision algorithm developed by the DAFW-UoM. This algorithm automatically finds the centroid and tracks the head movements in both axes (x and y), and four quartiles are considered. Furthermore, this algorithm can automatically extract all metrics and statistical data (means and standard deviation) of the abrupt head movements.

2.3. Face recognition and feature extraction using deep learning

The VisV was also used to recognize the face of the cows and extract the features, which were further used as inputs to predict the age of each cow. A total of 25 different video frames (one per second) from 89 cows were used for this model, these cows are a subset of the 102 cows used for biometrics analysis. The raw images were first used to detect the face location using YOLOv5 [20], followed by the landmark detection to align the face by rotating it to align the eyes and nose to a neutral

Fig. 1. Example of a video frame from one cow showing the eyes and nose areas identified and cropped to assess heart rate in beats per minute (BPM) and respiration rate in breaths per minute (BrPM), respectively.

position using anchorage points based on the eyes position and nose using Resnet18 [21]. Once the images were detected and aligned, the MobilenetV2 [22] face encoder was used to obtain the embedding features, consisting of a 1D array with 128 features. This process was developed in Jupyter Notebook (Project Jupyter, USA).

2.4. Information obtained from robotic milking unit

Data from each cow, which are stored in the collar, were obtained from the robotic milking system. These data consisted of (i) SCC (x1000), (ii) weight (kg), (iii) rumination (min), and (iv) feed intake (kg).

2.5. Statistical analysis and machine learning modelling

Data were grouped by age of cows for statistical analysis, in general terms, the numbers of cows used for the different ages are between three and 63 with a mean of 28 cows per age group. Analysis of variance (ANOVA) was conducted using XLSTAT 2020.3.1 (Addinsoft, New York, NY, USA) for feed intake, SCC, weight, and rumination along with Tukey Honest Significant Difference (HSD) *post hoc* test to assess significant differences between the age groups ($p < 0.05$; $\alpha = 0.05$). Multivariate data analysis was conducted based on principal components analysis (PCA) using the feed intake, somatic cell count, weight, rumination, HR, RR and abrupt movement data. A code written in Matlab® R2021a, which standardizes the data to develop the PCA, was used to assess relationships within variables and their association with cows of different ages.

Two ML models were developed using artificial neural networks (ANN). The ANN models refer to a non-linear method [23] which works by simulating the human brain's neural signaling and is able to identify and learn patterns among inputs and targets assigning weights and biases, making it capable of solving multi-target non-linear problems [24,25]. Most algorithms using ANN work with three stages, (i) training stage is used for fitting the model and train the weights of the ANN, (ii) validation stage uses a different set of samples to find the best network configuration and optimization of the model and, (iii) testing stage uses another set of samples, and its purpose is to evaluate the neural network obtained from the training and validation stages [26]. Sample sets used for each stage are independent of each other, this means that samples used in one stage are not used in the others. Finally, the overall accuracy considers the data (correct and miss classifications) obtained from the three stages and calculates a new accuracy, which considers the entire data set.

Model 1 was constructed using regression ANN with the biometric responses as inputs to predict (i) SCC, (ii) weight, (iii) rumination, and (iv) feed intake (Fig. 2). Levenberg Marquardt was selected as the best training algorithm after testing 17 different algorithms [27] using a code developed in Matlab® R2021a, which can test them in a loop. This selection was based on the highest accuracy for all stages (training, validation, testing, and overall), slope (b) of the model, and performance values, and no signs of under- or overfitting found. The total number of samples ($N = 282$) was randomly divided into $N = 150$ for model development and $N = 132$ for deployment. Data division was set to random, and the first set of samples ($N = 150$) were divided into 70% ($N = 104$) for training and 15% ($N = 23$) for each validation and testing stage. Given that four targets were used, the number of observations (data points) for training was 416, and 92 for each validation and testing stage. Performance was calculated based on the means squared error (MSE) algorithm. To overcome any under- or overfitting, different

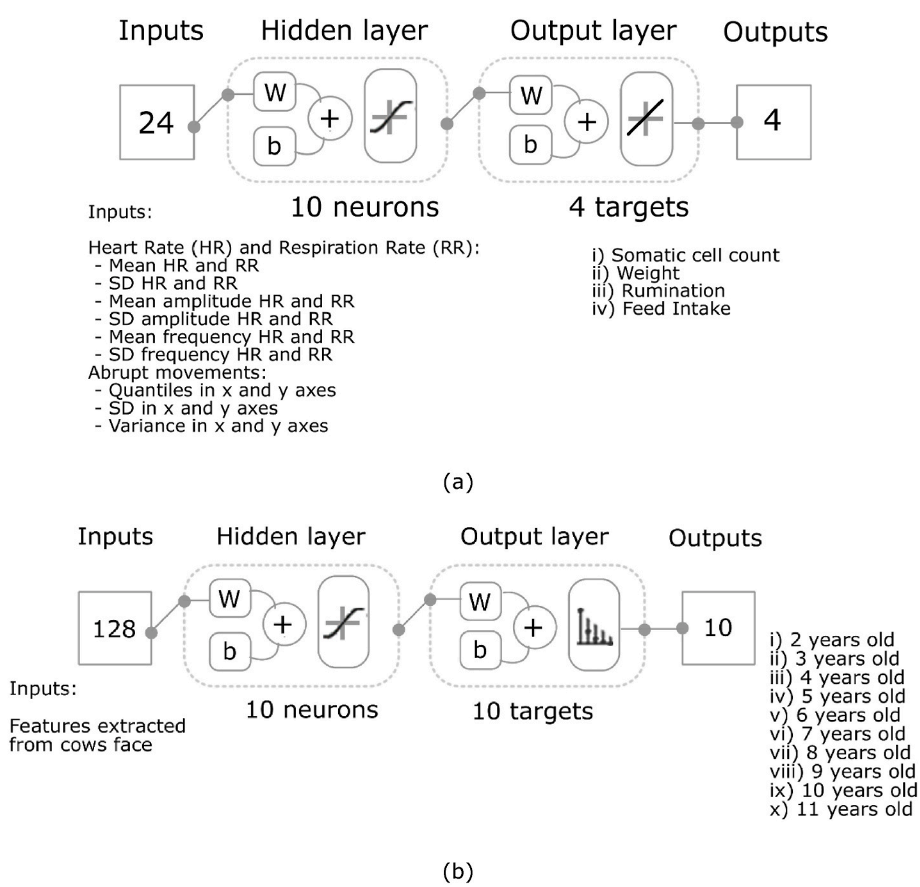

Fig. 2. Diagrams of the two-layer feedforward models with a tan-sigmoid function in the hidden layer and (a) a linear transfer function in the output layer for Model 1, and (b) a Softmax transfer function for Model 2. Abbreviations: W: weights; b: bias; SD: standard deviation.

numbers of neurons, which simulate the human brain function, were tested (3, 5, 7, and 10), obtaining the best model with 10 neurons.

Model 2 (Fig. 2b) was developed based on pattern recognition for classification using the 128 features extracted from the face of the cows as inputs to predict the cows' ages in a range from 2 to 11 years old. This model was constructed using the scaled conjugate gradient training algorithm, which resulted in the best of the 17 different algorithms tested based on performance and accuracy, as explained in Model 1. A total of 13 random frames from each video of 89 cows (N = 1157) were considered samples to develop the model. Samples were divided randomly as 70% (N = 809) for training, and 15% (N = 174) for each of validation and testing stages. Performance was calculated based on a cross-entropy. The use of different frames for this model was required because the cow moves, and this allows having the facial features from different angles, which allows accurate deployment results without the need for recording images in a specific position.

For Model 1, the second set of samples (N = 132) was used to evaluate the model and confirm its accuracy. Outputs were analyzed using ANN regression to test the correlation coefficient (R), and a scatter plot was developed, including the 95% confidence bounds to assess outliers.

Similarly, for Model 2, the second set of samples (N = 1068) using 12 different frames of each video from the 89 cows was used to evaluate the model and confirm its accuracy. Outputs were analyzed based on the correct classification of samples into the different age categories. A receiver operating characteristics (ROC) curve was developed to visualize the accuracy of the deployment.

Deployment for both models was developed using videos recorded on different days and conditions (weather and luminosity), and they were consistently accurate.

3. Results and discussion

Fig. 3 shows examples of output from videos of two different cows. It can be observed that cow one presented HR between 60 and 108 BPM and RR within 18 and 50 BrPM (Fig. 3a), while cow two had HR within 70 and 130 BPM and RR 20–51 BrPM (Fig. 3b). However, only the mean values were used for the models presented in this study, which are within 73–85 BPM for HR and 27–43 BrPM for RR. According to the literature, these HR and RR values are within the ranges expected for dairy cows (HR: 70–90 BPM; RR: 20–50 BrPM) [28–32]. Furthermore, the biometrics used to assess these parameters have previously been validated using contact sensors for cows [12,18], sheep [17], and humans [19]. From abrupt movements, Fig. 3c and d shows the normalized pixel variation from the centroid of cow head frames considering the initial head position as baseline, where values close to −1 mean minimum variation in x and y axes (minimum head movements) and 1 maximum variation in x and y axes (maximum head movements). It can be observed that cow one remained almost steady as there was a slight variation in movements within the x- and y-axis (Fig. 3c), while cow two moved more along both axes, but especially on the x-axis (lateral movements; Fig. 3d). Results from this study are in accordance with cow's abrupt movements that have been analyzed using similar digital tools in previously published research [12].

Fig. 4a shows that the feed intake for cows of different ages did not present significant differences ($p > 0.05$). Likewise, SCC did not present significant differences ($p > 0.05$) between cows of different ages. It is worth noting that no mastitis has been detected due to the levels of somatic cells detected by the RDF as, according to the literature, milk with <200,000 somatic cells is indicative of non-infected cows [33]. Fig. 4b shows significant differences ($p < 0.05$) between different ages for weight and rumination. It can be observed that cows 8 and 10 years old were the heaviest (653 and 654 kg, respectively), while the youngest cows (2 years old) had the lowest weight (508 kg). On the other hand, 5-year-old cows had the highest rumination time (428 min), while the oldest cows (11 years old) presented the lowest (302 min).

Fig. 5 shows that the PCA accounted for 62.06% of total data variability using principal components one and two (PC1 = 33.33%; PC2 = 28.73%). The total data variability is above the cut-off (>60%) required

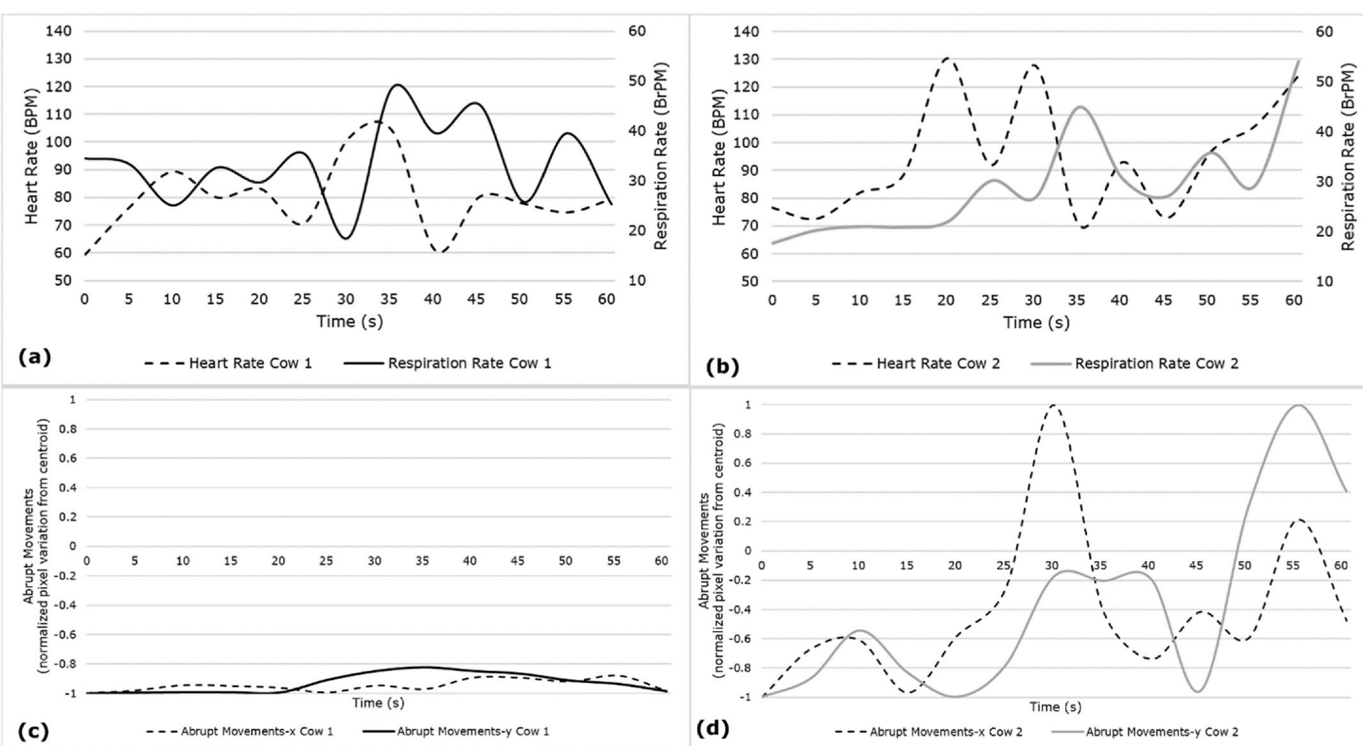

Fig. 3. Example and comparison of biometric outputs of two different dairy cows. (a) and (b) show the heart rate and respiration rate responses over time for cows one and two, respectively, while (c) and (d) show the abrupt movements in x- and y-axis for cows one and two, respectively, based on normalized pixel variation from centroid of cow head frames considering initial head position in x and y axes as baseline.

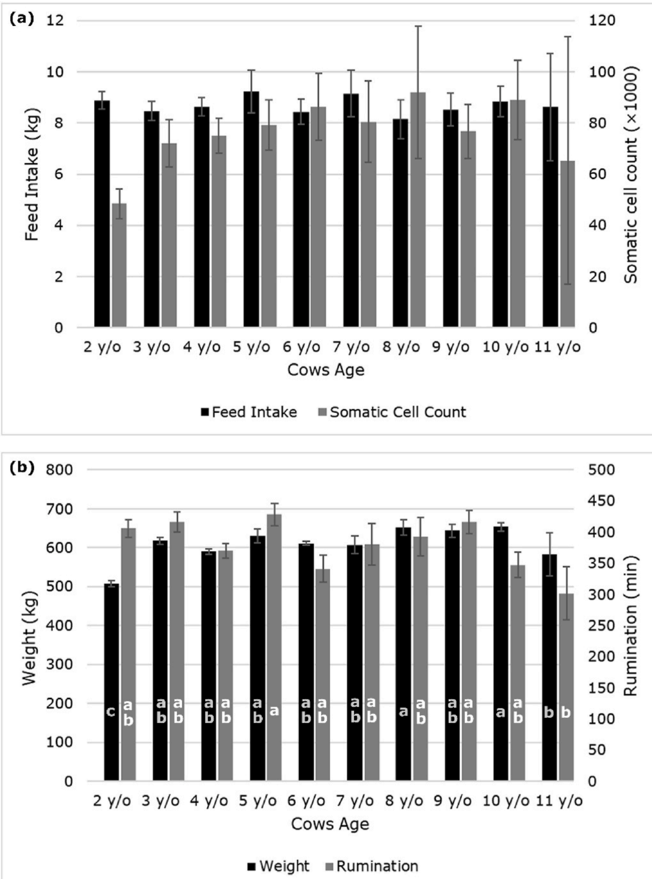

Fig. 4. Results from the cows information obtained from daily activity grouped by age, where (a) shows the feed intake and somatic cell count, and (b) shows the weight and rumination. Letters (a–c) within bars depict significant differences ($p < 0.05$) between age groups of cows based on ANOVA and Tukey Honest Significant Difference (HSD) post hoc test. Bars with no letters did not present significant differences ($p > 0.05$). Error bars were calculated based on standard error. Abbreviations: y/o: years old.

for the PCA to be significant [34]. According to the factor loadings (FL), PC1 was mainly represented by abrupt movements in the y-axis (FL = 0.51) and RR (FL = 0.43) on the positive side of the axis, and SCC (FL = −0.44) and weight (FL = −0.43) on the negative side. On the other hand, PC2 was mainly characterized by HR (FL = 0.58) and SCC (FL = 0.44) on the positive side and feed intake (FL = −0.09) on the negative side of the axis. This would be expected as elevated SCC or mastitis is likely to increase HR [35] and decrease feed intake [36,37]. It can be observed that there was a positive relationship between rumination and RR with cows 7, 3, and 9 years old associated with these parameters. It is unclear why HR and RR are related to rumination as the latter generally decreases during HS when HR and RR increase [38]. On the other hand, SCC and weight have a positive relationship, with cows 8, 5, and 6 years old associated with them. These variables also had a negative association with feed intake. Abrupt movements in x had a negative relationship with HR.

Table 1 shows that ML Model 1 presented very high accuracy (R = 0.96) in predicting SCC, weight, rumination, and feed intake using contactless biometrics. The model also had a high slope (b = 0.96) and no signs of under- or overfitting, given that the performance of the training stage had a lower MSE value (2251) than validation (MSE = 8166) and testing (MSE = 6167). Furthermore, the low number of neurons (10) and input parameters (24), which is lower than 70% of observations, contribute to having no overfitting of the model.

Fig. 6a shows the model with 95% prediction bounds, which

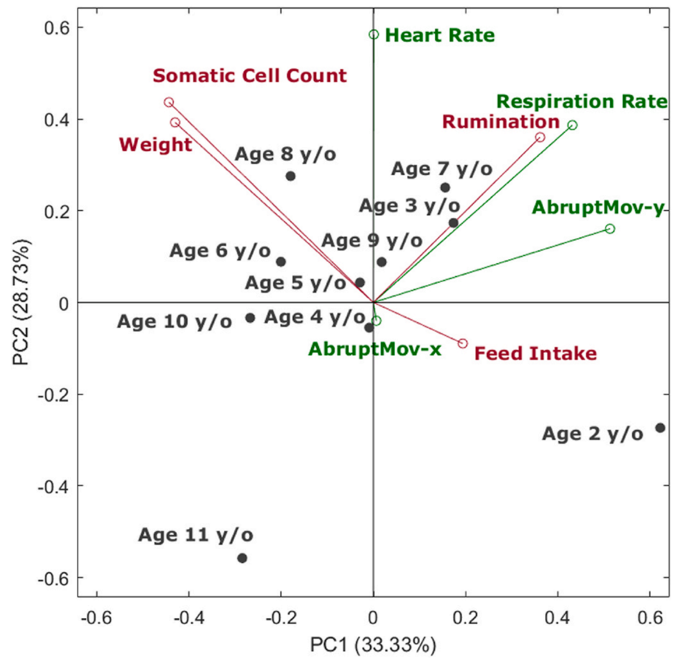

Fig. 5. Principal components analysis showing different variables for cows grouped by age. Abbreviations: PC1 and PC2: principal component one and two; y/o: years old; AbruptMov-x and AbruptMov-y: abrupt movements in x- and y-axis.

Table 1
Results from the machine learning Model 1 showing the correlation coefficient (R), slope (b), and performance based on means squared error (MSE) for each stage.

Stage	Samples	Observations (samples × targets)	R	b	Performance (MSE)
Training	104	416	0.98	0.98	2251
Validation	23	92	0.92	0.93	8166
Testing	23	92	0.94	0.93	6167
Overall	150	600	0.96	0.96	–

presented 5.67% of outliers (34 out of 600 observations), with the majority being for rumination (green squares). On the other hand, Fig. 6b shows the deployment of the model with data from 132 cows; in this figure, it can be observed that it had high accuracy (R = 0.93) and 5.49% outliers (29 out of 528 observations) also with the majority being for rumination.

Table 2 shows that Model 2 had a very high overall accuracy (98%) in predicting the age of the cows using the face features as inputs. The similar accuracies among all stages of the model, in addition to the close performance values from validation and testing and lower value for training, are indicators of no under- or over-fitting of the model.

Fig. 7 shows the results from the ROC curve of Model 2 (Fig. 7a) and its deployment using a different set of data (Fig. 7b). It can be observed that in the model, all categories are close to the highest true-positive rate, being 11 years old, the age category with the highest misclassifications or lowest true-positive rate (0.85). The deployment had an overall accuracy of 82%, with 11 years old as the lowest accuracy (0.67); this is due to the low number of samples used to develop and deploy the model for this category (one cow; 13 samples for the model; 12 samples for deployment) compared to the number of samples from other ages. However, the model may be retrained and improved in further studies to increase the sample for this age and include cows of different ages.

Model 2 for age prediction is important for traceability purposes. If any farmer buys a new cow, they can ensure they receive the animal

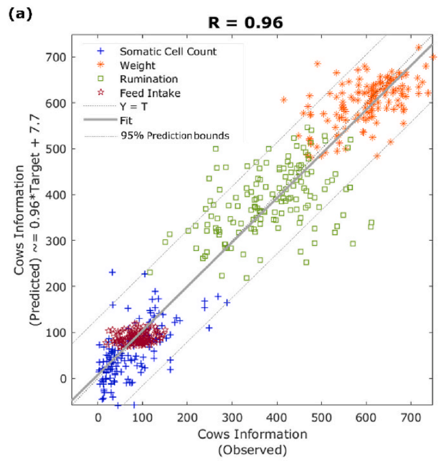

Fig. 6. (a) Regression model (Model 1) developed using data from 150 samples of dairy cows, and (b) deployment of the model using 132 different samples. Abbreviations: R: correlation coefficient; T: targets; cows information refers to the targets/outputs mentioned in the Figure legend.

Table 2
Results from the machine learning Model 2 to predict the age of the cows, showing the accuracy and performance based on cross-entropy.

Stage	Samples	Accuracy	Error	Performance (Cross-entropy)
Training	809	99.6%	0.4%	<0.01
Validation	174	93.7%	6.3%	0.02
Testing	174	92.5%	7.5%	0.03
Overall	1157	97.7%	2.3%	–

with the characteristics that the seller promises in terms of age to avoid fraudulent transactions, which are quite common everywhere.

This model was developed from videos in the crush to have better control for model training; however, the use of different frames and angles of the face allows to deploy it in any setting, not only a crush. Furthermore, the model may be automated so that when a new animal enters the herd, it is recognized as a new animal and adds the cow to the inputs; the farmer would need to incorporate the targets for the model to learn and include it within the database.

For this study, temperature from IRTI analysis was not included since it has been shown in previous studies that skin/eye temperature can be calculated as a proxy of HR and RR since the latter physiological parameters regulate body temperature in dairy cows [12,39]. Amongst the benefits of the proposed system (biometrics plus machine learning) consist of the fact that it only requires a conventional RGB video camera [12,17], the detection of animals and acquisition of results takes less than 1 s for animal recognition, and age and less than 8 s for welfare assessment (e.g., SCC, HR, weight, rumination, among others) [12,17], which is a great advantage for farmers to obtain several parameters in a short time, therefore, saving costs and labor.

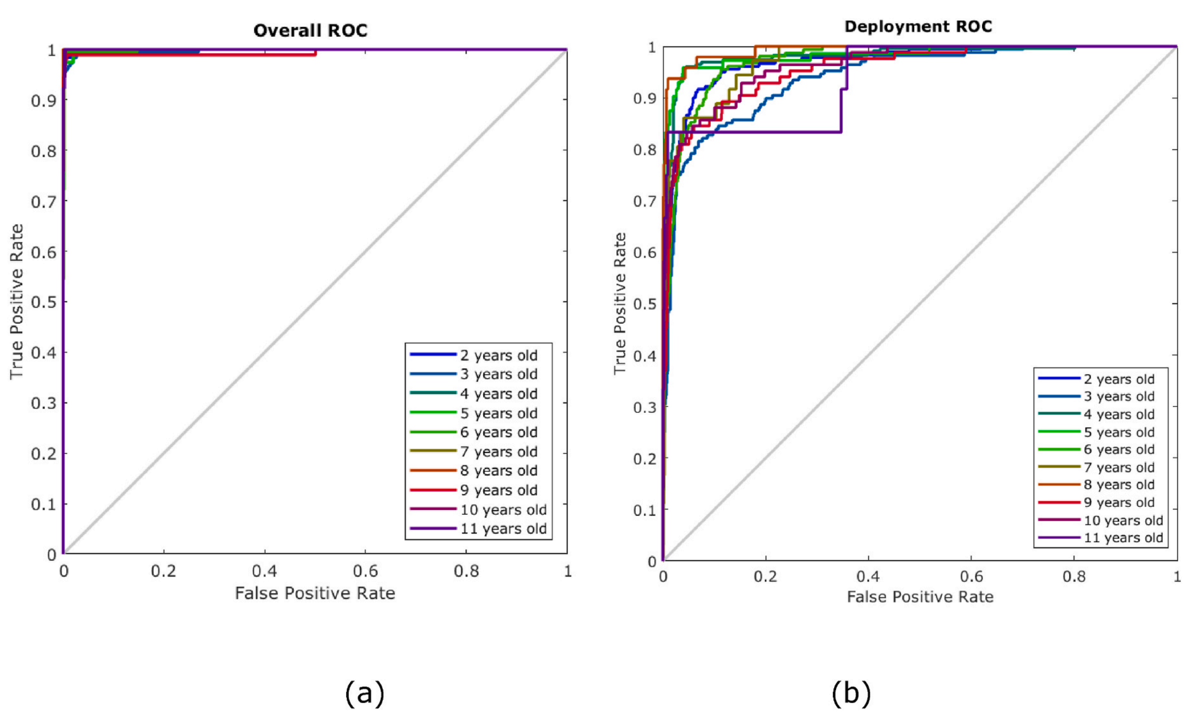

Fig. 7. Receiver operating characteristics (ROC) curves of (a) Model 2 develop with the first data set (N = 1157) and (b) the deployment of Model 2 using the second data set (N = 1068).

4. Conclusions

The ML models developed in this study can be used with a ubiquitous VisV camera, which could help to reduce the costs of assessing animal age and welfare parameters. These models can be deployed in parallel with other ML models previously developed can be added to the deployment system to have a complete animal identification, produce productivity, milk quality trait assessment, and welfare. The implementation of these models could also be used in conventional dairy farms by using a normal RGB camera, increasing the applicability of AI for livestock assessment and productivity. Further research is required to include other parameters that can be readily obtained to acquire the level of data and accuracy to develop accurate machine learning models.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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