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A novel low-cost visual ear tag based identification system for precision beef cattle livestock farming

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A B S T R A C T

The precision livestock farming (PLF) has the objective to maximize each animal's performance while reducing the environmental impact and maintaining the quality and safety of meat production. Among the PLF techniques, the personalised management of each individual animal based on sensors systems, represents a viable option. It is worth noting that the implementation of an effective PLF approach can be still expensive, especially for small and medium-sized farms; for this reason, to guarantee the sustainability of a customized livestock management system and encourage its use, plug and play and cost-effective systems are needed. Within this context, we present a novel low-cost method for identifying beef cattle and recognizing their basic activities by a single surveillance camera. By leveraging the current state-of-the-art methods for real-time object detection, (i.e., YOLOv3) cattle's face areas, we propose a novel mechanism able to detect the ear tag as well as the water ingestion state when the cattle is close to the drinker. The cow IDs are read by an Optical Character Recognition (OCR) algorithm for which, an ad hoc error correction algorithm is here presented to avoid numbers misreading and correctly match the IDs to only actually present IDs. Thanks to the detection of the tag position, the OCR algorithm can be applied only to a specific region of interest reducing the computational cost and the time needed. Activity times for the areas are outputted as cattle activity recognition results. Evaluation results demonstrate the effectiveness of our proposed method, showing a mAP@0.50 of 89%.

1. Introduction

Livestock products are the second most important source of food for the world's population, which continues to grow and to demand animal protein, especially in emerging countries [1]. Despite the limitations in terms of environmental resources and skilled personnel, the global cattle sector is tasked with meeting this growing need. Within this context,

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it becomes crucial for the entire production process, to develop the ability of farmers to locally monitor both the productivity and the welfare of their animals [2].

Based on intelligent perception, key body indicators with high precision obtained for individual animals can help farmers evaluate animal welfare, health, and productivity throughout their life cycle, and design management strategies efficiently. Continuous monitoring of the varying needs of each individual animal is a core of precision livestock farming (PLF); the aim is both to optimize the individual contribution of animals and to achieve high efficiency of livestock farming while keeping costs and environmental footprint low, and ensuring the quality and safety of livestock products [3].

In particular, identification and tracking of each cattle can be a tool available for better disease control and focused interventions, resulting in an improved animal survival and a significant reduction in antibiotic use. A low-cost and reconfigurable PLF visual system for monitoring individual beef cattle would enable innovation even in those settings that have a large environmental impact (i.e., a huge number of small/medium farms).

In this paper we focus on the development of a low cost, single-camera identification system able to identify each calf through its assigned ID and to recognize the pose in front of the water drinker (i.e., drinking state, non-drinking state) in order to provide daily "per animal" reports of the cattle drinking behaviour (i.e., visits number, total time, water volumes,. . .).

Intelligent perception for animal monitoring was coined by Kendrick in the late 1990 s ([4]). It refers to the perception of animal body information in their daily environments by merging multimodal data as well as to the ability to learn and analyze the animal health status [3]. Recently, a variety of smart devices, i.e., RGB-D cameras [5] or IoT wearables [6,7], have become available for monitoring each animal in real-time. In [8], the authors proposed a Deep Learning-based approach to segment individual cattle for animal monitoring.

Systems to assess movements such as collars or earrings, equipped with RFIDs or accelerometers, are recently used in dairy cows; due to the crowded environment and the typical intemperance of beef, any system hanging from the animal can be easily damaged if not properly protected, also leading to injuries. For this reason, biometrics and visual characteristics of livestock have emerged as an alternative promising approach for animal identification [9]. Muzzle patterns, retina/iris patterns, and facial and body coat characteristics are the three current biometric identifiers of livestock.

Although significant progress has been achieved, many applicability issues still exist due for instance to the need for skilled personnel for RFIDs system installation and management, or the difficulty of capturing images from moving cattle and the illumination influence, just to name a few. Since deep learning has found widespread application in object recognition and image feature extraction, this technology has recently been utilized to identify livestock without requiring the acquisition of specific images of each observed individual animal. Traditional computer vision image classification algorithms have been proposed to recognize animals in an image obtaining an overall accuracy that has been outperformed by recent deep Learning based algorithms [10].

Despite the above progress in vision and deep learning-based cattle identification, most of the existing methods focus on dairy cattle [11] with limited work targeting beef cattle that present more challenging uniform coat colours. In [12] cattle are recognised as unknown individuals through system-generated ID numbers that could be on one hand performant when we aim at identifying the observed cattle's general behaviour, on the other hand, it cannot identify and name the individual animal as when a focused intervention is needed. The focus in [13] is the individual cattle rear recognition through the movement analysis; they use a convolutional neural network (CNN), and a long short-term memory (LSTM) network with a reported accuracy that spans from 88 % to 91 %. Despite some approaches propose more visible collars with digit numbers [14], conventionally, plastic ear tags are used to identify individual cattle; in [15] and [16] are proposed different OCR algorithms applied on offline devices to recognise the handwritten character from different people and with a different style. The same authors in [17] propose the use of the ear tag ID to identify the cattle; the head is detected and tracked by using a pre-trained YOLO detector model by achieving an accuracy of 92.5 % in recognising individuals Within this context we propose a simple plug and play deep-learning-based scheme to monitor cattle in the stable, as described in the next section.

By leveraging the current state-of-the-art methods for real-time object detection, we trained and validated our dataset on a pre-trained YOLOv3 [18] that belongs to the popular real-time Convolutional Neural Network family of models for object detection. The proposed methodology can, for instance, be used to report the time each animal spends in front of the manger (or estimate the water and feed intake) or to monitor the total visits within the day or to correlate feeding behaviour changes with other programmed habits changes. The beef cattle farm for both training and testing the proposed approach, is in Monastier (TV), in the northeast of Italy. The training video sequences are acquired during both day and night-time with acquisitions in two different stables and from different camera installations. The animal IDs are automatically read through an Optical Character Recognition (OCR) algorithm [19] for which, a specific error correction algorithm is here presented to avoid numbers misreading and correctly match the IDs to only actually present IDs.

The paper is organized as follows: in Section 2 the materials and proposed methods are described; the experimental results are shown in Section 3 and Section 4 provides the conclusions.

2. Materials and methods

We here propose a new low-cost method to identify cattle and recognize basic activities by using a single low-cost surveillance camera. The cattle are recognized by a deep learning detection system: every time the animal goes to the drinker, heads and ear tag areas, drinking or not drinking actions, are recognized separately at the same time. Among the analysed cattle, ear tag ID numbers are detected to identify the

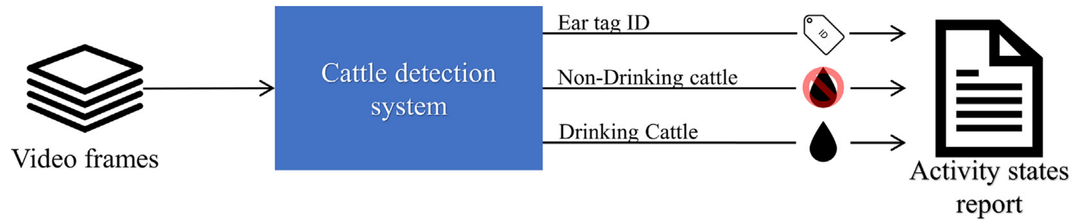

Fig. 1 – Outline of the proposed approach.

animal and kept to the following frames of the video for which the animal is still recognised at the drinker. Activity times for the areas are outputted as cattle activity recognition results. The outline of the proposed approach is illustrated in Fig. 1. The drinking (i.e., head down with the muzzle inside the drinker) or not drinking (i.e., head up) actions can be defined as when the animal has the head down into the drinker or when the head is completely outside the drinker respectively, as shown in Fig. 2.

2.1. *Hardware setup*

The system installation and experimental setup were made in a Charolais cattle farm in Monastier (TV) North-East Italy from 30th October 2020. One of the four stalls used for the quarantine period of the calves just arrived from France was used for the test. Each box can accommodate from 24 to 28 calves, and it has a window with a drinking trough where a maximum of two calves can visit simultaneously. The Google COLAB cloud platform [20] was used for pre-processing and modelling the proposed system that was first tested on videos recorded previously. Then it has been installed and tested on real-time videos. Videos were recorded at a rate of 15 fps and a resolution of 1 920 × 1 080 pixels, each video with a length of 1 h. The infrared vision of the chosen surveillance camera guarantees a good quality even with low light conditions, thus allowing the system to read the ear-tag also during the night time as shown in the top pictures in Fig. 2.

The hardware configuration (see Table 1) comprised a SP007 Sricam IP waterproof camera (Oba Srl, Italy) with an IR Night Vision (minimum illumination 0.01 lx, IR LED lights), and a single-board computer Nvidia Jetson Xavier AGX, linked together through a network switch equipped with an ADSL network connection. It is worth noting that, by switching to a slower framerate, an even cheaper solution can be obtained by considering instead of the Jetson Xavier AGX, the entry-

Fig. 2 – Example of system identification results during different moments of the day (during the nighttime in the top pictures; during the daytime in the bottom pictures). It's also shown how the system can discern from "drinking" activity (red square) from the "nondrinking" activity (green square). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1 – Devices used in the implementation of the system. Main characteristics and price of the devices.

Device	Information	Price
Sricam sp007	• resolution 1920x108015 fps • H.264	49.99€
Switch TP-Link TL-SG1008P	• 8 ports (4 Poe)	51.40€
Jetson Xavier AGX	• GPU volta 512 core • CPU ARM 8core v8.2 • MEM 32 Gb 256-Bit LPDDR4x | 137 GB/s • STORE 32 Gb	699.00€
Total		800.39€

level single-board computer like Raspberry PI 4 (92.00€ for kit) or Jetson nano (240€ for kit); in this case, the lower RAM capacity could be compensated by training a Tiny-YOLO model [21] that features small size (<50 MB) and fast inference speed (it achieves upwards of 244 FPS on a single GPU).

The chosen physical camera setting is the optimal compromise between image quality, the ear tag framing and the specific environmental constraints; the side view was chosen to both impede the calves to damage it and to minimize the possible backlighting in the images. The camera was positioned at approximately 1.6 m from the ground and 1.0 m from the drinking through, it was mounted on an aluminium bracket in front of the drinker and oriented to get a complete view of the window with the drinking through.

2.2. *Detection method*

To recognize calves in stalls with fast computational performance and robust identification, The You Only Look Once version 3 (YOLOv3) method was used [18] as starting point; YOLOv3 is a multiscale object detection network with a more robust feature extraction framework than previous versions based on convolutional neural networks (CNNs), as well as improved loss function computation. The first step is the feature extraction: an input frame/image is first sent through the Darknet-53, a deep convolutional neural network with 53 layers. The feature extraction step produces three feature maps, each of which subsamples the original input image by 32, 16, and 8 times from its original size, respectively. The actual detection kernels are then produced by passing these feature maps through 53 additional fully convolutional layers of the Object Detector module of the YOLOv3 network. YOLOv3's final architecture is a 106-layer deep neural network that generates detections at three distinct scales (using previously created feature maps of various sizes) to allow reliable detection of objects of various sizes. The system was trained and validated according to the scheme reported in Fig. 3.

The images dataset used in the net training was obtained from a random choice of the frame in the videos acquired in heterogeneous light conditions, both during day and night.

As shown in Table 2 a total of 1 507 frames were used for both training and testing the model. To “normalize” the environment the frames were converted to grayscale images, then manually labelled to indicate ear tag ID areas, drinking cattle head state, and non-drinking cattle head state as depicted in Fig. 4.

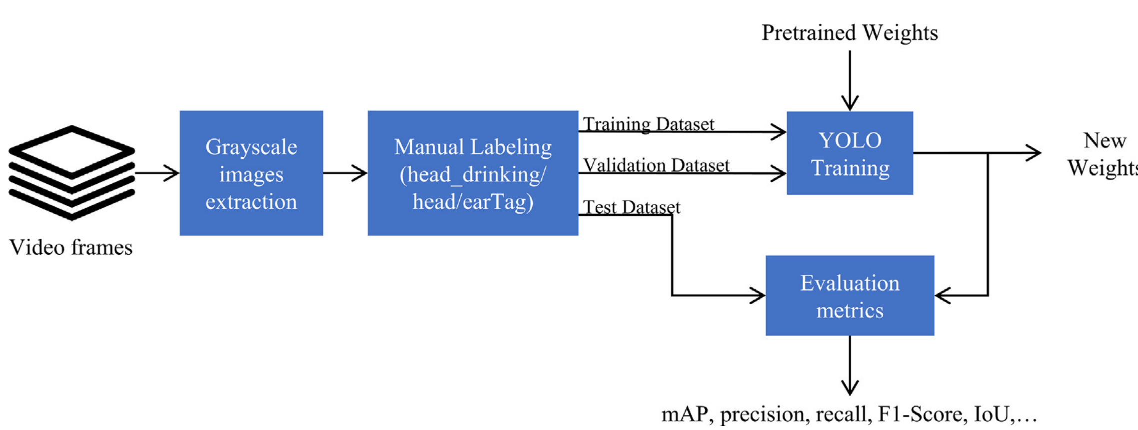

Fig. 3 – Custom YOLO net training and evaluation process.

Table 2 – Images dataset subdivision in training, validation, and test.

Dataset	Class	Images per class	Labels per class
training_images_identification:	Empty images	329	–
Total images: 1270	Calf face	512	528
train 890, validation 380	Tag	366	412
	Calf face drinking	442	461
test_images_identification:	Empty images	85	–
Total images: 237	Calf face	91	94
	Tag	58	74
	Calf face drinking	64	65

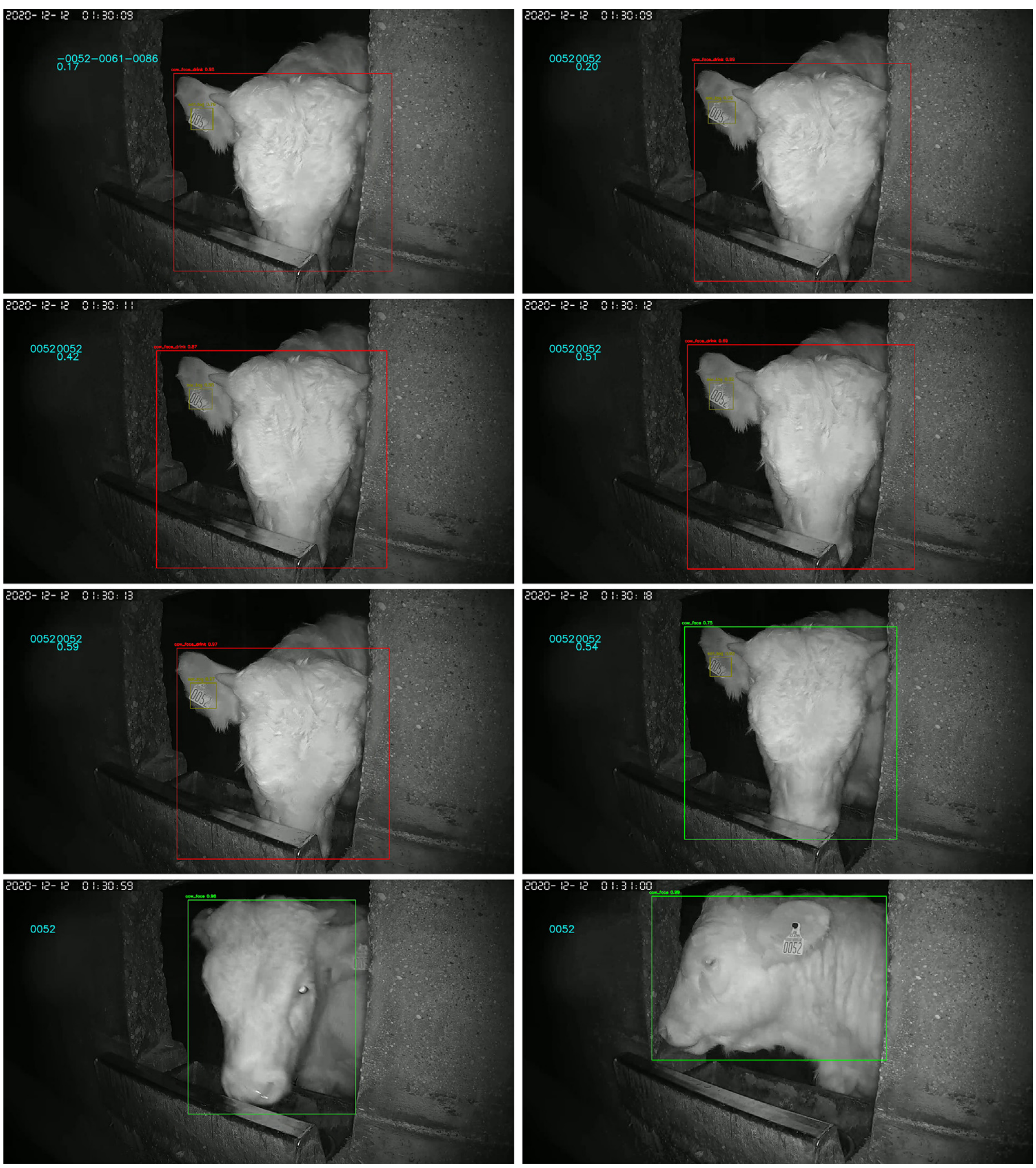

Fig. 4 – Refinement process of a tag number reading in a frame sequence. Green squares indicate a nondrinking head recognition. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

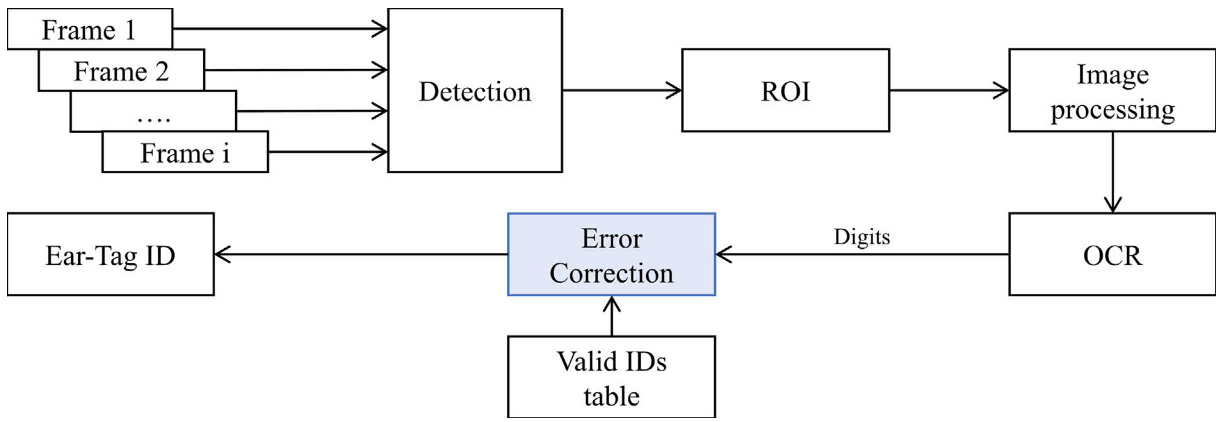

Fig. 5 – System flow for head, detection and ear-tag confirmation.

We applied YOLOv3 to detect the regions of interest containing drinking actions and the bounding box containing the ear tag based on the visual appearance of the calf when framed in the camera.

To measure the net performance, we referred to the metrics for the evaluation of convolutional neural network architectures reported in [22]. The *precision* is the evaluation of misidentification of object presence $\frac{TP}{TP+FP}$. The *recall* is the evaluation of misidentification of object presence $\frac{TP}{TP+FN}$. The $F1-score$ is $\frac{2*precision*recall}{precision+recall}$, i.e., the comprehensive evaluation of predicting object presence. *IOU* stands for Intersection Over Union, equals to $\frac{Overlapping\ area}{Union\ area}$ and allows the evaluation of the deviation between the ground truth pixels area and the predicted area. *FN* is the false negative. *TP* is true positive, and *FP* is false positive.

2.3. Ear tag ID recognition and error correction algorithm

As indicated in Fig. 5, the identification system first step is the calf head and the ear tag ID localisation within the frame using the custom YOLO net obtained at the training step. For each frame, when detected, the ear tag comes with its bounding box coordinates. To reduce the computational time, only the region of interest (ROI) with the ear tag is considered as input to the OCR algorithm (Easy OCR [19]). To better isolate the digits to be recognised, the ROI image is pre-processed by first performing a gaussian blur filter, then spotting the digit shape (i.e., structuring elements) and performing some closure and opening (i.e., erosion-dilation cycles) (see Fig. 6).

Due to the head position, ear hair overlapping or other kinds of occlusions, the OCR could recognise only partially the 4-digits code thus allowing a misreading of the ID as also reported in [17], in which a similar identification/tracking scheme is proposed to search cattle by providing their ID. For this reason, we propose to introduce an ID-aware mechanism to make the overall identification and action recognition system more robust and reliable even when applied in challenging environments as in the case of beef cattle farms.

To improve the reading, the system is equipped with a valid IDs aware mechanism (see Fig. 7) that relies on a predefined table containing only the used IDs. Such table is considered as input to the proposed error correction algorithm that, together with the read digits predicts the correct ear tag ID.

At the first frame of the analysed sequence, the recognised digits are compared against the IDs in the valid IDs table (i.e., the Look-Up Table, LUT), and all the eligible IDs are assigned temporarily to the considered frame.

Each eligible ID has given a score that is incremented at each frame reading, proportionally to the number of the actually read digits (see Fig. 8).

Fig. 6 – Pre-processing of the ROI with the detected ear tag ID.

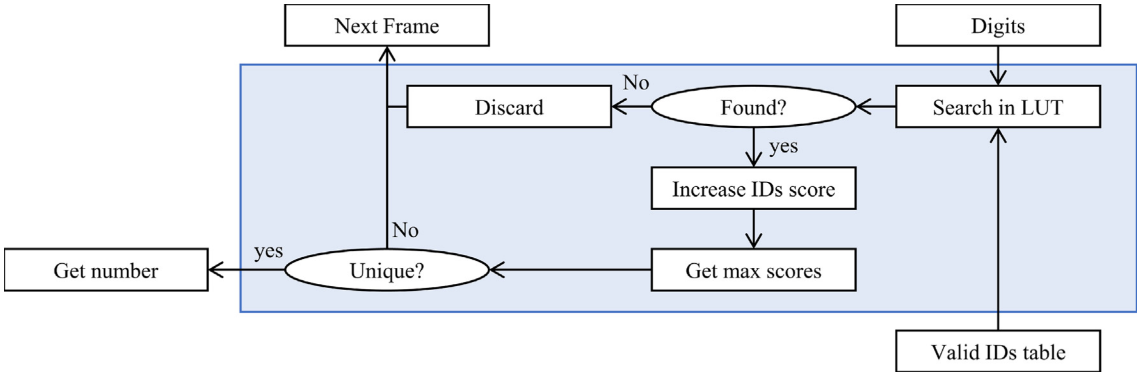

Fig. 7 – Error correction algorithm flow.

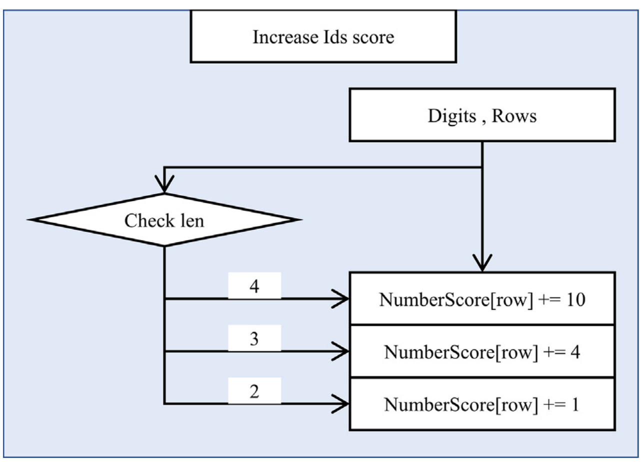

Fig. 8 – Increase IDs score flow.

Then, at each frame reading, the maximum score among the candidates IDs is calculated; if the maximum score corresponds to a unique ID in the LUT, such ID is assigned to the entire analysed sequence from the beginning (or backwards to the previews uniquely identified ID); otherwise, if the maximum score belongs to more than one ID in the LUT, the next frame is considered for processing until the unique valid ID is found for the sequence.

As said, for each frame, the identification system outputs (when detected), not only the ear tag bounding box but also, (when detected) the state of non-drinking or drinking head detection. When a head is found in the frame, the ear tag ID is assigned according to the algorithm described above. The continuous presence of the calf at the drinker is confirmed until a head is detected in the frame even if the ear tag is not visible/detected in the while (see Table 3).

3. Experimental results

In Fig. 9 is depicted the average precision (AP) for all three detection models. AP is the average performance of misidentification of object presence for a single class. In animal heads recognition, the AP was over 95 %. As reported in a recent state-of-the-art review [9] the identification performance of our proposed model, is aligned with the widely used deep learning models for precision beef cattle farming (i.e., precision values in the range 85.6 % and 99.2 % for the YOLO-based approaches). The ear tag detection average precision is 76 % on the trained net and 66 % on the test dataset. It is worth noting that the ear tag detection underperforms compared to the head detection, this is mainly due to several reasons, for example due to the fur occlusion or the smaller size of the ear tag compared to the calf head together with the ear mobility resulting in blurred pixels in the ear tag region.

The system was validated on a separate test dataset and several metrics were considered to assess the system's effectiveness (Table 4).

While the two datasets provide similar results in terms of AP in the detection of the calves' heads, the ear tag detection shows a significant decrease in performance, probably due to the chosen test dataset that includes video frames in which the times the ear tags contour is occluded, is higher than in the training/validation dataset.

Table 3 – Correlation between head detections in a sequence and ear tag read number.

Frame #	Ear-tag detected	OR (Face/DrinkingFace)
...	✗	✗
i	✓	✓
i + 1	✗	✓
...	✗	✓
i + N	✓	✓
i + N + 1	✗	✗
...	✗	✗

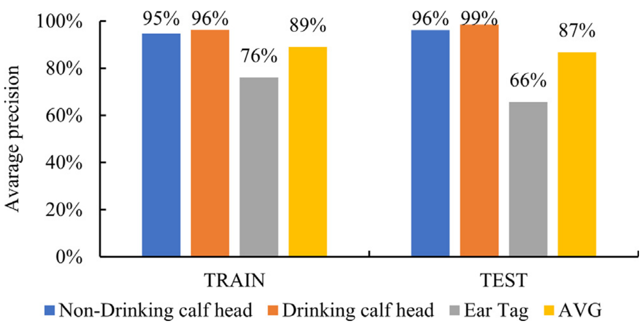

Fig. 9 – Average precision of the trained net and average precision on a test dataset for the three classes.

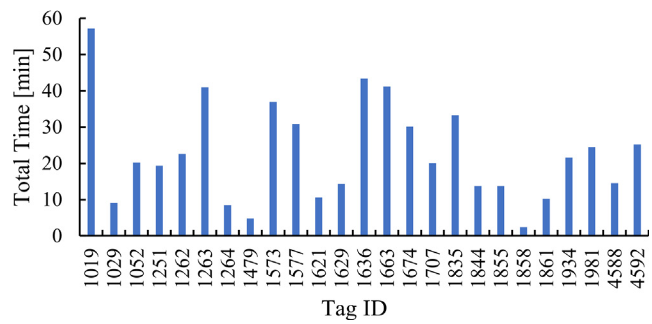

Fig. 11 – Individual time spent at the drinking through during the 24 h.

As an example, in Fig. 11 it is reported the total time spent at the drinker for each individual; it is clear as some individuals spend more time than others at the through.

The time spent at the drinker can be distinguished between drinking time and nondrinking time as depicted in Fig. 12.

Considering that cattle can drink from 12 L/min up to 20 L/min of water [23] the minimum and the maximum water consumption for each cattle is calculated from the total amount of drinking time during the day. The total average consumption of water goes from a minimum of 81 L/day up to 135 L/day for each animal. In Fig. 13 is shown the estimated quan-

Table 4 – Evaluation of the performance of the proposed model.

Metrics	VALIDATION	TEST
Precision	90 %	88 %
Recall	87 %	84 %
F1-score	88 %	86 %
Average IoU	74 %	72 %
TP	380	195
TN	44	27
FP	58	38
Mean average precision (mAP@0.50)	89 %	87 %

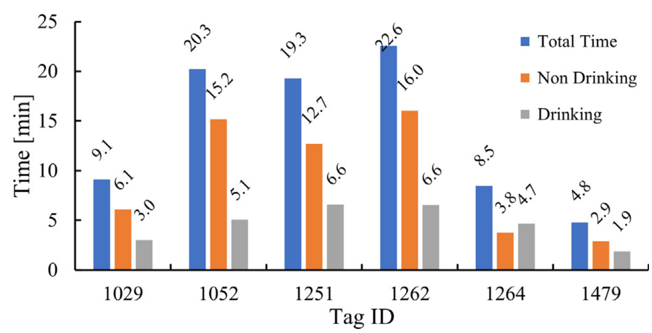

Fig. 12 – Time spent at the drinker for some individuals; in orange the standing/nondrinking time and in grey the actual drinking time. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The reliability of the proposed correction strategy is reported in terms of misdetection and false alarm rate (i.e., wrong id detection). The comparison has been performed by manually checking the actual calves' IDs at the drinking through in the analysed video and comparing the annotation with the system output for a 24 h video. Still 22 % of the IDs are lost by the system, but 71 % of the IDs are result of both the correct ID reading and the application of the correction mechanism. Only 7 % of the IDs are misdetected.

The activity states reports are depicted in the following figures. In Fig. 10 it is reported the total time (the sum of each individual) spent at the drinking through that the cattle perform during the 24 h; visits are higher, as expected, after the feeding time (07:30–08:30, 16:30–17:30); of course, by performing the same analysis for each animal, the veterinarians could predict some irregular behaviour and make a decision on the single calf.

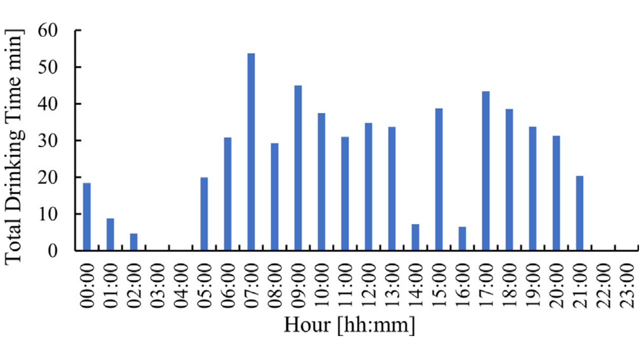

Fig. 10 – Total time spent at the drinking through during the 24 h.

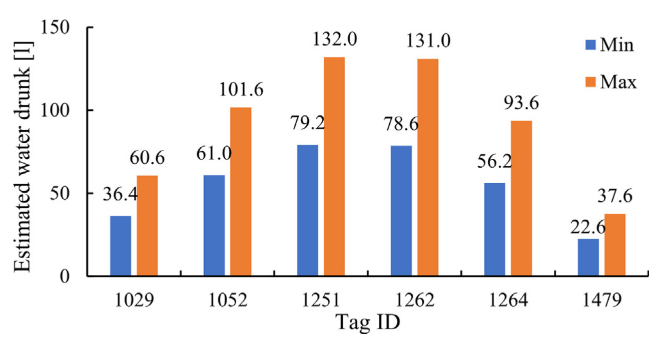

Fig. 13 – Estimation of water drunk by some individuals during an entire day of monitoring.

tity of water drunk for some of the monitored cattle. As reported in [24] and [25] the total amount of water drunk by beef cattle with an air temperature of 21 °C (maximum temperature measured by the system during the day) can reach 55 L/day. As we can see the average drinking behaviour of the barn is in line with expected values. Values out of the expected range may be a sign of disease in some individuals.

4. Conclusions

In this paper, we proposed a low-cost system able to guarantee high performances in detecting and recognizing cattle in their daily environment. We defined a complete scheme for the visual identification of the ear tag ID of framed individuals from a single low-cost camera; the cattle drinking actions are also detected and tracked to output per animal drinking activity monitoring reports. An improved ear tag detection and ID reading mechanism are proposed to detect and track the calf head. In heads recognition, the average precision of the proposed convolutional neural network was over 95 % for both two classes. The identification performance of our proposed model is aligned with the widely used deep learning models for precision cattle farming (i.e., precision values in the range of 85.6 % and 99.2 % for the YOLO-based approaches).

The proposed IDs correction algorithm shows a true positive rate of 71 %. The comparison has been performed by manually checking the actual calves' IDs at the drinking through in the analysed video and comparing the annotation with the system output for a 24 h video. Still 22 % of the IDs are lost by the system, but 71 % of the IDs are result of both the correct ID reading and the application of the correction mechanism. Only 7 % of the IDs are misdetected.

Examples of activities reports are also provided to analyse herd drinking behaviour or to alert individuals focused interventions and comparison with the expected water daily consumption is given.

This system can highly improve the monitoring of the beef cattle behaviour, giving useful information distinguishing the effective time spent drinking water from the time spent at the drinking trough without drinking. Also, to perform a more comprehensive precision cattle farming solution, the system could be coupled with a top-view surveillance camera able to extend the identification of the ear tag ID triggered at the drinker to track the overall cattle covered distance during the 24 h and measure the visits and the time spent at the manger.

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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