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Evaluation of two computer vision approaches for grazing dairy cow identification*

Evaluación de dos enfoques de visión por computadora para la identificación de vacas lecheras en pastoreo

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ABSTRACT

Computer vision is being used in Precision Livestock Farming to monitor and analyze animal health, behavior, and productivity. However, the implementation of these technologies faces technical challenges that require collaboration between farmers, researchers, and technology providers. In this study, the performance of two different grazing dairy cow identification approaches was compared using a ResNet-based computer vision model. The first approach consisted of image classification, while the second approach was based on the comparison of features or embeddings. The YOLOv5 model was used to detect and classify cows in images captured with three high-definition cameras on a dairy farm. A database consisting of two main folders: "TRAIN" and "TEST" was generated based on 19 Holstein dairy cows. Each folder contains 19 subfolders numbered from 001 to 019, corresponding to each cow. The approaches for the identification of cows were trained and validated using 4740 and 2256 images, respectively. FastAI was used for training the ResNet50 model in the first approach and the open-source PyTorch ReID project in the second. Validation tests of the models trained with the approaches were performed and the results were compared using a confusion matrix and five performance metrics. The results indicate that the embedding comparison approach performed significantly better in all validation tests compared to the image classification approach. This suggests that the embedding comparison approach is a more robust and accurate technique for the identification of Holstein cows under diverse conditions, which has great potential for its application in the implementation of automated monitoring systems for dairy farms. In summary, this study shows that computer vision is a valuable tool to improve the productivity and health of animals in Precision Farming.

KEYWORD:
Precision Livestock Farming; ResNet; FastAI; PyTorch ReID; Image classification; Embedding comparison; Computer vision; Behavior; Automated monitoring systems; Grazing.

RESUMEN

La visión por computadora se está utilizando en la Pecuaria de Precisión para monitorear y analizar la salud, el comportamiento y la productividad de los animales. Sin embargo, la implementación de estas tecnologías enfrenta desafíos técnicos que requieren la colaboración entre agricultores, investigadores y proveedores de tecnología. En este estudio, se comparó el desempeño de dos enfoques diferentes de identificación de vacas lecheras en pastoreo utilizando un modelo de visión por computadora basado en ResNet. El primer enfoque consistió en la clasificación de imágenes, mientras que el segundo enfoque se basó en la comparación de características o embeddings. Se utilizó el modelo YOLOv5 para detectar y clasificar las vacas en imágenes capturadas con tres cámaras de alta definición en una finca lechera. Se generó una base de datos que consta de dos carpetas principales: "TRAIN" y "TEST" con base en 19 vacas lecheras de la raza Holstein. Cada carpeta contiene 19 subcarpetas numeradas del 001 al 019, correspondientes a cada vaca. Se usaron 4740 y 2256 imágenes para entrenar y validar los enfoques, respectivamente. Se empleó FastAI para el entrenamiento del modelo ResNet50 en el primer enfoque y el proyecto de código abierto de PyTorch ReID en el segundo. Se realizaron pruebas de validación de los modelos entrenados con los enfoques y se compararon los resultados utilizando una matriz de confusión y cinco métricas de desem-

PALABRAS CLAVES:
Pecuaria de Precisión; ResNet; FastAI; PyTorch ReID; Clasificación de imágenes; Comparación de embeddings; Visión por computador; comportamiento, Sistemas de monitoreo automático, Pastoreo.

peño. Los resultados indican que el enfoque de comparación de embeddings tuvo un rendimiento significativamente mejor en todas las pruebas de validación en comparación con el enfoque de clasificación de imágenes. Esto sugiere que el enfoque de comparación de embeddings es una técnica más robusta y precisa para la identificación de vacas Holstein en condiciones diversas, lo que tiene un gran potencial para su aplicación en la implementación de sistemas automatizados de monitoreo para granjas lecheras. En resumen, este estudio muestra que la visión por computadora es una herramienta valiosa para mejorar la productividad y la salud de los animales en la Pecuaria de Precisión.

INTRODUCTION

Computer vision is a field of artificial intelligence that focuses on enabling machines to interpret and understand visual data, as humans do, from the outside world (Gollapudi and Gollapudi, 2019). Computer vision algorithms can be used to analyze and interpret images and videos, extracting meaningful information and insights from data. In Precision Livestock Farming (PLF), computer vision can be used to monitor and analyze animal behavior and health, recognizing and tracking individual animals within a herd, managing feed, and optimizing agricultural practices to improve productivity and efficiency (García *et al*., 2020). This use of technology allows farmers to improve animal welfare, reduce labor costs, and to minimize environmental impact.

However, the implementation of these technologies has not come without challenges (Neethirajan and Kemp, 2021). A significant barrier for the implementation of these technologies is the cost of outturn and maintaining computer vision systems, including the use of sensors and big data analysis. Additionally, farmers may be reluctant to implement data-driven agriculture approaches, preferring traditional empirical or experience-based management practices instead. Another challenge is ensuring the privacy and security of data generated by computer-based technologies, this not come at ease and requires extra implementation of often costly and complicated procedures. Integrating data from multiple sources is also difficult, especially when different data formats and platforms are used. Regulatory frameworks that support and incentivize the adoption of PLF technologies are required, along with the validation of their effectiveness and reliability at large scale. Ensuring interoperability between different systems and devices is also a critical challenge for digitization in livestock production. Addressing these challenges is the key to unlock the full potential of PLF technologies and improving the efficiency and sustainability of the livestock sector, for the benefit of both producers and consumers.

To address these challenges, it is necessary for farmers, researchers, and technology providers to collaborate in developing solutions that address technical, economic, social, and regulatory barriers. Universities can play a key role in promoting initiatives that foster the adaptation of technologies to each country's particular conditions. For instance, one of the major challenges in the implementation of computer vision in the livestock se°ctor in grazing-based countries is the development of accurate and reliable algorithms for the identification and tracking of grazing animals.

Computer vision algorithms and models used for animal identification and tracking in PLF may vary depending on specific applications and the animal species being detected. These models and algorithms can be classified into two groups, one based on the use of artificial intelligence and the other based on morphological characteristics of the subject combined with algorithms and databases. The first approach is to use convolutional neural networks (CNNs) and deep learning techniques, which have demonstrated high accuracy in image and video recognition and classification (Albawi *et al*., 2017). The latter approach is based on methods that extract specific features or attributes of the animal's appearance, such as color, texture, and coat shape, and once a match on the appearance is obtained, it uses matching algorithms to identify and track individual animals based on those features and on a reference database constructed for the task (Kumar *et al*., 2015; Kumar *et al*., 2017; Okura *et al*., 2019).

The most used CNN model for image classification is the Residual Network (ResNet) architecture (Jafar and Lee, 2021). ResNet was developed by Microsoft researchers in 2015 (He *et al*., 2016) and has become a popular choice for a variety of computer vision tasks, including object recognition (Lu *et al*., 2019), image classification (Mahajan and Chaudhary, 2019), and facial recognition (Peng *et al*., 2020). What makes ResNet special is that it has a way of "remembering" important features of the image, even if they are far apart in the network, this helps ResNet make more accurate predictions and perform well even with very large and complex images (He *et al*., 2016). Overall, ResNet is a powerful tool for analyzing and understanding visual data and possesses many applications in fields such as medicine (Zhou *et al*., 2022), engineering (Zhang and Zhou, 2019), and agriculture (Hu *et al*., 2020).

In this study, the ResNet50 model was used to individually identify dairy cows in video images. Two different approaches were implemented to achieve this goal. In the first approach, the model was trained to classify dairy cow images based on their identification numbers. This means that the model learned to recognize the visual characteristics and patterns of each cow and to assign it to a specific category. In the second a model was used to calculate the similarity between images of unidentified cows and images of the same cows that were previously identified. This was achieved by extracting and comparing the features of the unidentified cow images (embeddings) with the embeddings of the identified cow images. In this way, an efficient and accurate dairy cow identification system was developed using ResNet50 in two different approaches. This paper aims to evaluate two computer vision approaches for the identification of grazing dairy cows.

METHODS

Data acquisition

This work was carried out at the Agricultural Practices and Development Center "La Montaña" owned by the University of Antioquia, located in the municipality of San Pedro de los Milagros (Antioquia, Colombia). The agroecological conditions of the area are 2468 meters above sea level, a temperature of 14,5 °C, relative humidity of 79,7 %, and an annual average precipitation of 2923 mm, corresponding to a lower montane wet forest life zone (bh-MB).

Three high-definition cameras were used to capture images of grazing cows, positioned at a height of three meters and different angles in two grazing zones of "La Montaña" with a distance between cameras of 25 meters. The cow herd consisted of 19 lactating animals. The pasture area where they were grazing during the measurements averaged 1400 m^2 with a flat topography. The cameras were programmed to take photos every 30 seconds for a period of 30 minutes between 16:30 to 17:30 h. To increase the variety of animal positions and lighting conditions, image capture was carried out on two consecutive days.

Extraction and classification of images by cow

The YOLOv5 (You Only Look Once) model was used. YOLOv5, an open-source research from Ultralytics (https://ultralytics.com/), is an object detection model that has the ability to detect and locate multiple objects in an image, including cows in this case. Once the cows are detected, the area of the corresponding image for each cow is cropped, eliminating any background or irrelevant objects, and the cropped images are saved as separate files. To automate this process, Python scripts written by Ultralytics were used, which took the output from the YOLOv5 model and performed the cropping and saving automatically. In addition, information from nearby and individual videos of the cows involved in the study was used to correctly classify the extracted images.

Training of the model

The ResNet50 model was trained twice using two different approaches: a) one for image classification, where the model was trained to recognize and classify individual cows based on their characteristics, and b) one for feature extraction, where the model was trained to extract high-level representations of the input image without performing any classification or labeling. The same training images were used for both approaches.

For the first approach, FastAI (Howard and Gugger, 2020) was used. The training process involves several steps. First, the images are loaded using a 'DataBlock' object, which defines how to convert the data into a format that can be used for training. In this case, the data is loaded using the 'get_image_files' and 'parent_label' functions to extract the image files and their labels (cow number from 001 to 019) respectively. The data is randomly split into training (80 %) and validation (20 %) sets using the 'RandomSplitter' function. The images are transformed using 'RandomResizedCrop' to obtain images of 224x224 pixels, and the data batches are augmented using the 'aug_transforms' function. The 'DataLoaders' object is created using the 'DataBlock' object and is used to load the data into the model during training. The model is created using the 'cnn_learner' function, which takes as input the 'DataLoaders' object, the architecture of the convolutional neural network (in this case ResNet50), and the evaluation metric ('error_rate'). Finally, the model is trained using the 'fit_one_cycle' method, which trains the model for a specified number of epochs (in this case 20) with a specified learning rate (3e-3 in this case). During training, the model adjusts its weights based on the loss calculated during forward and backward propagation (Rumelhart *et al*., 1986). The training and validation loss are shown during training, and the model is saved at the end of training in the '*.pkl' format.

For the second approach, the open-source PyTorch ReID project (https://github.com/layumi/Person_reID_baseline_pytorch) was used. This is a library for person re-identification based on the PyTorch deep learning framework. The "train.py" file of this project creates two datasets, "train" and "val", from the images supplied by the user. The images in these datasets are preprocessed using the "data_transforms" function, which applies transformations such as resizing, cropping, and normalization to the images. Next, the code creates two data loaders, "train" and "val", using the datasets created earlier. These data loaders load the images in batches, where each batch contains a specified number of images (32 in this case). The "shuffle" parameter is set to "True", so that the images are loaded in a random order to help prevent the model from overfitting to specific patterns in the dataset. The code then defines a "train_model" function, which is used to train the deep learning model. This function takes the ResNet50 model, the criterion (the loss function), the optimizer (the optimizer used to adjust the weights), and the scheduler (a torch.optim.lr_scheduler LR scheduler object that adjusts the learning rate during training). The function then runs a specified number of epochs (20 in this case) and trains the model with the "train" and "val" datasets. During the training process, the LR scheduler and optimizer are used to adjust the learning rate and update the weights of the model. Finally, the function returns the trained model, which is saved in "*.pth" format at the end of training.

Validation of approaches

For this, the same images were used in both approaches. The validation images were not used in training the models.

For the image classification approach, the "predict()" function from the FastAI library was used. Initially, the model was loaded from the "model.pkl" file. The test folder path is set in a variable and a list of all the folders within that path is obtained. Then, the code iterates over each folder in the list and, for each folder, obtains a list of images within the folder. Then, for each image, a prediction is made using the loaded model, and the prediction result is added to a Python list (for example, named "predicted"). Additionally, the actual class value (which is in the folder name) is added to another Python list (for example, named "real"). After the code has gone through all the images in all the test folders, two lists will have been collected: one with the actual class values and another with the values predicted by the model. These two lists are finally used to calculate the confusion matrix and various evaluation metrics of the model, such as accuracy and recall.

In the embedding comparison approach, two steps were taken to validate the model. In the first step, the "test.py" file from PyTorch ReID was used to extract the embeddings from the training and validation images. During this process, a function called "extract_feature" takes the previously trained model and images to extract features from the images (embeddings). The function takes as input the model and a "DataLoader" object containing image data. The function iterates over each batch of images (32 in this case) in the DataLoader and, for each batch, does the following: a) Passes the images through the model to generate their embeddings, b) Performs normalization operations on the outputs, c) Concatenates the normalized outputs for each batch of images, and d) Returns a tensor containing all the extracted features from all the images in the dataset. Additionally, the "get_id" function extracts label information from the images. The obtained embeddings are saved in separate ".mat" files, one for the training images and another for the validation images.

In the second step, the Python class called "rank()" was used with two methods: "sort_img()" and "rank_result()". The "rank_result()" method uses the previous methods to generate a list of the five most similar images to a query image and returns the most common label of these images, along with the original query label. In the "sort_img()" method, the training images are sorted based on their similarity with the queried validation image. To do this, the similarity score between the query image and all training images is calculated using dot product, which is a mathematical operation that takes two vectors and returns a scalar. Then, the training images are sorted in descending order based on their scores and the sorted list of training images is returned, from the most similar to the least similar. This way, the number of cows in each cow image in the validation images can be estimated. As in the previous approach, two lists were generated: one for actual identifications and another for predicted identifications to calculate the confusion matrix and various evaluation metrics of the model, such as accuracy and recall.

Comparison of approaches

To compare the results of the two ResNet50-based approaches and identify their strengths and limitations for the identification of dairy cows in grazing, a confusion matrix was used. A confusion matrix is a table that summarizes how many observations were correctly or incorrectly classified by the model. The matrix is a square table with rows representing the actual class and columns representing the predicted class. The diagonal elements of the matrix represent the number of correct predictions for each class, while the off-diagonal elements represent the incorrect predictions.

In both approaches, the respective confusion matrix was used to calculate the following performance metrics: a) Accuracy: measures the proportion of cases in which the model has correctly predicted the class of an object in relation to the total evaluated objects. It is defined as true positives / total objects, b) Precision: measures the accuracy of the model in classifying a specific class. It is defined as true positives / (true positives + false positives), c) Recall: measures the ability of the model to find all positive cases. It is defined as true positives / (true positives + false negatives), d) F1 score: combines precision and recall into a single metric. It is calculated as the harmonic mean of precision and recall. It is defined as 2 * (precision * recall) / (precision + recall), and e) Matthews correlation coefficient (MCC): measures the quality of binary classification that takes into account true positives, true negatives, false positives, and false negatives. The MCC value varies between -1 and 1, where -1 indicates a completely incorrect classification, 0 indicates a random classification, and 1 indicates a perfect classification. An MCC value of 0.5 or higher indicates good classification. MCC is defined as: $MCC = (TP \times TN - FP \times FN) / \sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}$, where TP = true positives, TN = true negatives, FP = false positives, and FN = false negatives.

To construct the confusion matrices, the “crosstab()” function of the Pandas library (McKinney, 2010) was used, and the “accuracy_score”, “precision_score”, “recall_score”, “f1_score”, and “matthews_corrcoef” functions of the “sklearn.metrics” library (Pedregosa *et al*., 2011) were used to calculate the metrics.

RESULTS

Database

A database of 19 Holstein dairy cows was created, consisting of two main folders: “TRAIN” and “TEST”. Each folder contains 19 numbered subfolders from 001 to 019, corresponding to each cow. All photos taken by each respective cow are located in each subfolder. The names of individual files include the cow number, the camera number where the photo was taken, and an order number (for example, “001_c1s1_02084.png”). Although only three cameras were used, camera numbering from “c1s1” to “c6s1” was used to meet the technical requirements of training the model with PyTorch ReID code. Individual files are images in “png” format with a constant height of 224 pixels and a variable width. Table 1 shows the number of images per cow and the cameras used for training and validating the models. As shown in Table 1, all cows were photographed by at least two cameras.

Table 1. Number of images per cow and cameras in the “TRAIN” and “TEST” folders of the database.

Cow	TRAIN		TEST	
	Camera	No. Images	Cameras	No. Images
1	c1, c2, c4	134	c5, c6	235
2	c1, c2, c3	459	c5, c6	55
3	c1,	347	c2	184
4	c1, c2, c3	243	c4, c5, c6	98
5	c1, c2, c3	201	c4, c6	62
6	c1, c2, c3	134	c4, c6	42
7	c1	346	c2	73
8	c1, c2	270	c3	25
9	c3, c4	118	c6	82
10	c3, c4	97	c6	131
11	c1, c2, c3	313	c4, c5, c6	190
12	c1, c2, c3	419	c4, c5, c6	240
13	c1, c2	245	c4, c5	30
14	c1, c2, c3	310	c4, c5, c6	131
15	c1, c2, c3	443	c4, c5, c6	281
16	c1, c2, c3	140	c4, c5, c6	111
17	c1	49	c2	42
18	c3, c4	38	c5, c6	49
19	c1, c2, c3	434	c4, c6	195
	Total	4740	Total	2256

Comparison of approaches

Figure 1 shows that the embeddings comparison approach had significantly better results in identification than the image classification approach. Overall, it can be observed that the embeddings comparison approach had fewer problems identifying the cows (cows 001, 004, 015, and 017) than the image classification approach.

Table 2 shows that the embeddings comparison approach achieved higher precision, suggesting better performance in terms of overall classification accuracy. The "Average Precision" was calculated using the precision of all classes. The result suggests that the second approach (embeddings) was more accurate in its positive predictions. The "Average Recall" was calculated using the recall of all classes. The embeddings comparison approach had a higher average recall, suggesting that it was better at identifying positive cases. The average F1 score was higher for the embeddings approach, suggesting that this approach is more balanced in its precision and recall. Finally, the Matthews Correlation Coefficient (MCC) indicates that the second approach was better at predicting both positive and negative cases.

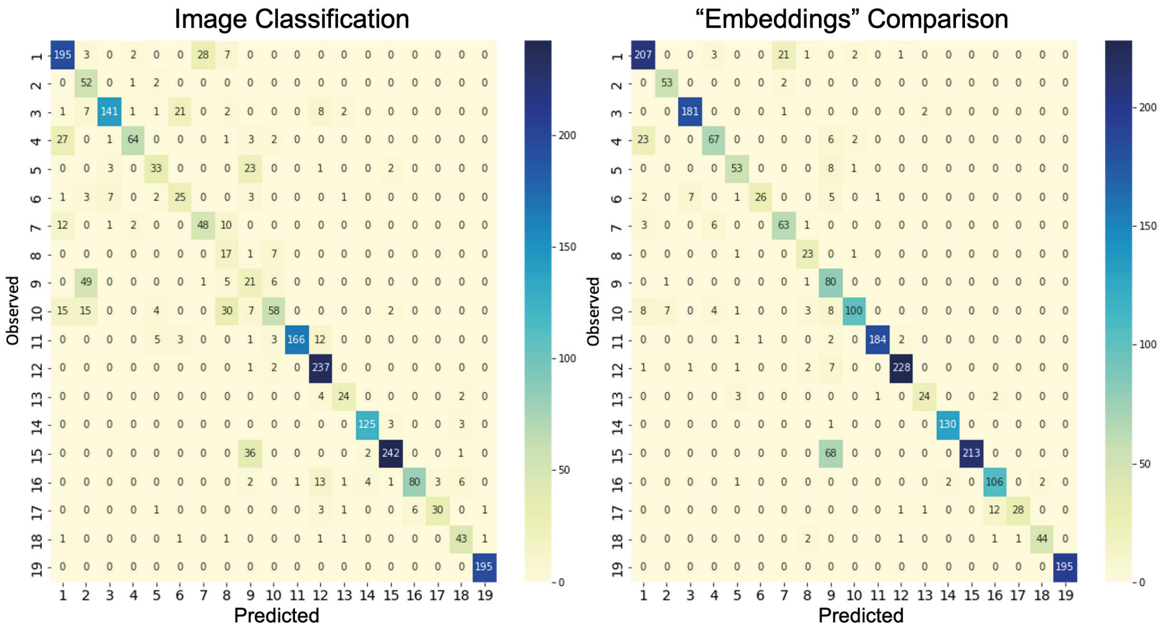

Figure 1. Confusion matrices for Image classification and "Embeddings" comparison approach for dairy cow identification.

Table 2. Comparison of the performance of the two approaches: image classification and embeddings comparison.

Metric	Image classification	"Embeddings" comparison
Accuracy	0,796	0,889
Precision average	0,746	0,882
Recall average	0,744	0,868
F1 "score" average	0,727	0,863
MCC	0,781	0,882

MCC: Matthews Correlation Coefficient.

Figure 2 presents some cases where the embeddings comparison approach failed to identify the cows. These errors could be due to high similarity between cows from certain camera angles (A), partial occlusion with objects between the cow and the camera (B, C), prioritization of the animal silhouette for embeddings generation (D), and a reduced number of images per cow (E, F).

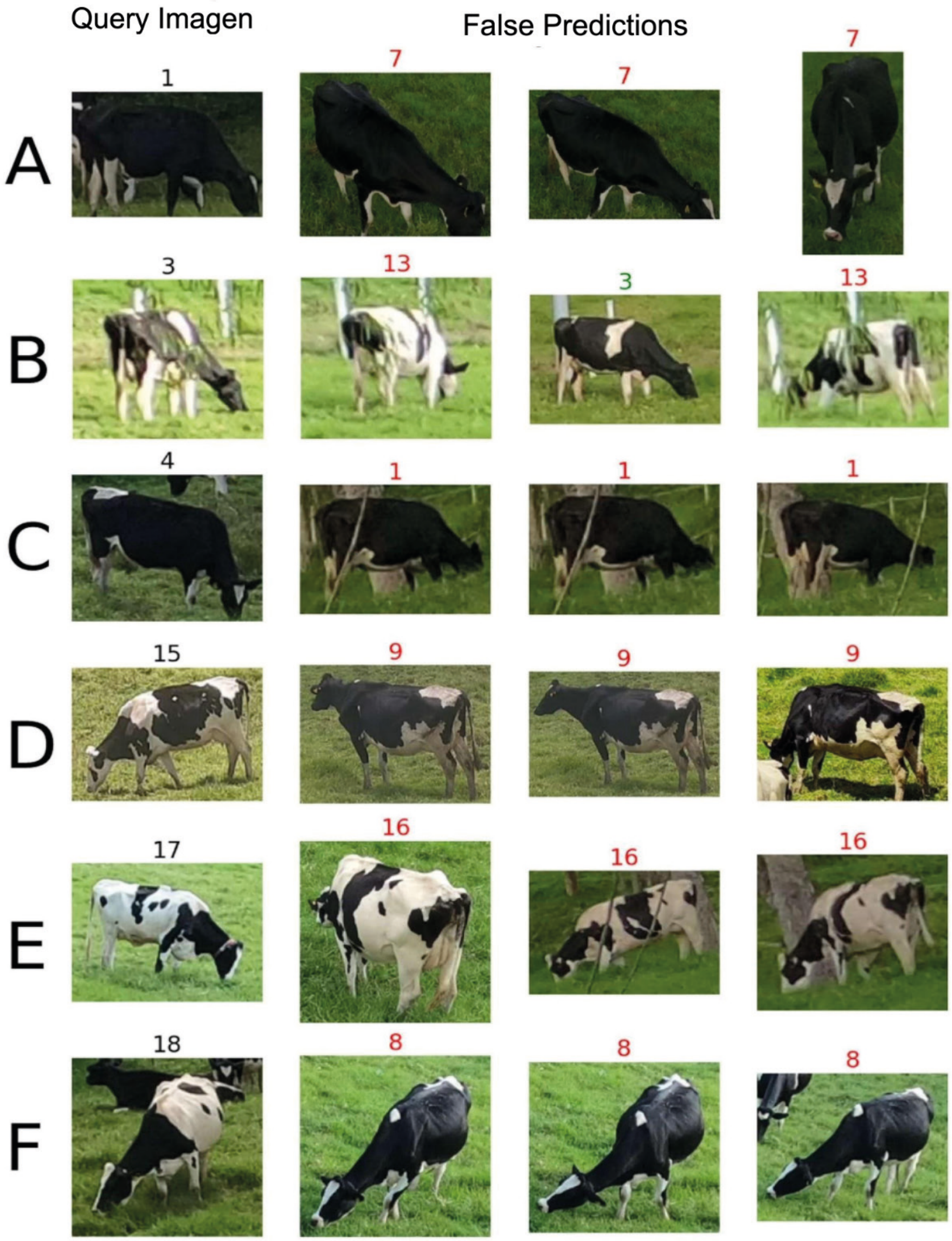

Figure 2. Examples of prediction errors using the embeddings comparison approach. Each row of images shows the query image on the left and the top three detections. The cow numbers appear above each image to indicate which one was expected to be the correct identification.

Livestock and agriculture are fundamental activities to ensure food security worldwide. However, these practices also have a great impact on the environment, which has led to the need to implement more sustainable practices in these sectors (Wijerathna-Yapa and Pathirana, 2022). Precision agriculture and precision livestock farming are two innovative approaches aimed at reducing the environmental impact of food production.

In the case of precision livestock farming, advanced technologies such as individual animal identification and animal behavior monitoring are used to improve herd management and reduce environmental impact. Individual animal identification allows for more precise monitoring of the health and behavior of each animal, which can help detect diseases early reducing the use of antibiotics and other medications, improving production efficiency, and potentially contributing to the reduction of environmental impact of livestock production (Lovarelli *et al*., 2020).

Precision approaches are closely related to the sustainable development goals established by the United Nations. Sustainable development goals related to agriculture and livestock include reducing hunger and poverty, improving nutrition, promoting sustainable agriculture, protecting biodiversity, and reducing the effects of climate change (United Nations). Therefore, the implementation of precision agriculture and livestock farming is important as it can significantly contribute to achieving these goals.

Precision livestock farming is a field that is constantly evolving, and technology is playing an increasingly important role in improving the efficiency and profitability of the sector. Artificial intelligence (AI) is a technology that is being increasingly used in the field (Bao and Xie, 2022). These technologies allow producers to analyze large data sets and make decisions based on accurate and real-time information, which can significantly improve the efficiency and profitability of livestock production.

One way in which AI is being used in precision livestock production is through monitoring animal behavior and health (Schillings *et al*., 2021). Sensors placed on the animals can collect data on their activity, location, temperature, and other factors, allowing producers to monitor animal health and detect problems early (Lee and Seo, 2021). AI can also analyze large data sets to identify patterns and trends (Rabah, 2018), which can help predict problems and improve decision-making regarding animal feeding and breeding. These technologies are driving the development of more sustainable and resilient agricultural production, which is essential to feed a growing global population and ensure food security in the future.

However, integrating technology into livestock production can seem like a daunting task for many farmers (Hostiou *et al*., 2017). The complexity of systems and high initial cost can be significant barriers to the adoption of precision technologies in animal production. Moreover, the lack of technical knowledge and training on how to implement and use technology can be another significant challenge for producers. Another challenge is the lack of infrastructure and connectivity in rural areas. Many rural areas lack access to high-speed internet (Ruiz-Martínez and Esparcia, 2020), which can limit the ability of farmers to use precision technologies such as sensors and monitoring systems. Additionally, the unreliable electricity supply in some rural areas (Mantilla *et al*., 2008) can limit the ability of farmers to use technologies that have a high energy demand, such as robots and automated feeding systems.

To address these challenges, it is necessary for developers of precision technologies to work closely with farmers to understand their needs and offer solutions tailored to their specific circumstances. It is important to offer training and technical support to farmers to help them implement and use precision technologies effectively, and the development of government policies that help address challenges and promote the adoption of these technologies.

Of the wide range of technologies applicable to the livestock sector (Bao and Xie, 2022), computer vision can help address some of the technical challenges mentioned. For example, individual animal identification can allow for more precise monitoring of animal behavior and health, which in turn can help prevent diseases and improve production efficiency. Additionally, individual identification can be useful for phenotypic classification, selection, and breeding of high-quality animals. However, individual identification is a laborious and costly task for farmers, making it necessary to develop low-cost automatic systems that support producers in this specific task. To fix this problem, computer vision technologies can be a solution. In this sense, this study compared two computer vision approaches for the identification of dairy cows in grazing: image classification and feature comparison or embeddings. Both approaches involve training an AI model using a large dataset of images to recognize and analyze specific image characteristics. In the case of image classification, the model is trained to recognize and classify images based on their features, such as colors, shapes, and textures. In contrast, for embeddings comparison, the model is trained to identify high-level features or patterns within the images and transform image data into a set of numerical values, known as embeddings, that capture the essential features of the image. These embeddings can be used to determine the similarity between a classified image and an unidentified one (Fan *et al*., 2019).

This study has several significant contributions in the field of computer vision for the livestock sector. First, two different approaches were compared for the individual identification of dairy cows in grazing, and it was found that the embeddings comparison approach had better performance than the image classification approach. This suggests that feature comparison can be a more robust and accurate technique for individual animal identification under diverse conditions. Second, a database of Holstein dairy cow images was developed, which could be useful for future research in the field of computer vision. This database could be used to train deep learning models for the individual identification of cows and other tasks related to animal health and behavior in dairy herds.

Overall, the database meets the requirements for being considered a good database for dairy cow identification, as it has the following characteristics: a) Sufficient variability: The database contains a wide variety of images of the same cows captured under different lighting conditions and camera angles. This helps the re-identification algorithm to be resistant to changes in the appearance of the cows, b) High quality: The images in the database have good resolution and are free of blurring, noise, and other artifacts. This helps the algorithm to extract and compare features accurately, c) Large size: The database is large enough to contain multiple instances of each cow in the dataset. This helps to reduce the probability of false positives and increases the identification algorithm's accuracy, d) Annotated: The database is correctly labeled with the corresponding identity of each cow. This is necessary to evaluate the performance of the re-identification algorithm and train machine learning models, and e) Balanced: The database is mostly balanced in terms of the number of instances for each cow in the dataset. This helps to avoid biases towards frequently occurring cows and improves the overall performance of the algorithm.

Thirdly, this work contributes significantly to the livestock sector since deep learning techniques and open-source tools such as PyTorch ReID and FastAI were used to train and validate the model in the two approaches. This could motivate researchers and industry professionals to use these tools and techniques in future computer vision and precision livestock farming projects. The use of APIs, such as FastAI, and open-source tools, such as PyTorch ReID, in this study is a demonstration of how technology can democratize access to innovation and research. In the past, the use of advanced machine learning and computer vision techniques required specialized skills and expensive computational resources. However, nowadays, with access to open-source tools, even people with little programming experience can venture into this field and develop innovative solutions. The use of open-source tools in research also fosters collaboration and knowledge sharing among researchers and professionals from different sectors. This is especially important in the livestock and precision agriculture industry, where the implementation of technological solutions may be limited by a lack of technical knowledge and computational resources.

Regarding the use of computational resources, it is important to highlight that in this work, Google Colab was used to train and validate the two identification approaches. Google Colab is a free online tool that allows users to run

Python code in a collaborative notebook environment based on the cloud. This tool is useful for training machine learning models as it provides free access to computing resources such as CPU, GPU, and TPU, which can be expensive in a local environment. Additionally, it also offers access to a variety of Python libraries and data visualization tools that can aid in the development of machine learning solutions (Google Colaboratory, 2022).

CONCLUSION

The results obtained in this study are significant for the livestock industry as they demonstrate that the embedding comparison technique is highly accurate and robust for identifying dairy cows in pasture. These findings suggest that the technique has significant potential to be applied in the implementation of automated monitoring systems for dairy farms, thus improving the efficiency and accuracy of the animal identification process.

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