Facial recognition of nelore cattle through computer vision

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Resumo

This article aims to develop a model for recognizing Nelore cattle based on images of their faces. The experiment employs a methodology involving the creation of a database of images containing 2,210 images of 47 Nelore cattle, along with identification annotations for each animal and facial segmentation information using the YoloV8 network. For recognition, the article utilizes feature extraction through embeddings with the Inception network. Finally, an analysis of the following machine learning algorithms is conducted: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Decision Tree (TREE), with precision values of 0.952, 0.987, and 0.635, respectively. This research is significant in the field of animal science as it proposes na innovative approach to Nelore cattle recognition using computer vision and machine learning technologies, contributing to more efficient and accurate

Keywords

Machine learning; Artificial intelligence; Nelore; Precision Livestock Farming,

1. Introduction

The exploration of beef cattle farming activity in Brazil is essentially based on Nelore cattle due to their adaptation characteristics to the country's tropical conditions [6]. Efficient herd management, ranging from individual monitoring to disease control and genetic improvement, is essential for the success of this activity. In this context, individual identification of Nelore cattle is a premise of precision livestock farming [16]. Recognizing cattle through images of their faces emerges as an innovative solution, enabling individualized monitoring and precise recording of each animal's information. This research proposes a methodological approach that combines computer vision technologies, deep learning for feature extraction, and machine learning for classification [18]. Automating the Nelore cattle facial recognition process can bring improvements in herd management, traceability, and inspection processes to ensure quality. Furthermore, animal identification and traceability align with the requirements of importing markets and niches that value the certification of beef origin.

The topic has been addressed by several research groups [11, 14], revealing the increasing importance of computer vision technologies, machine learning, and neural networks in these applications [17]. Furthermore, these studies emphasize the relevance of sustainability and animal welfare in modern livestock practices.

Despite the difficulty in acquiring face images during livestock handling, this is an alternative that can be employed in specific situations such as exhibition and inspection animals or the use of technology embedded in handling equipment such as waterers, feeders, chutes, and scales.

According to the Food and Agriculture Organization of the United Nations (FAO), around 1.3 billion people depend on livestock production for their livelihoods, and these proteins constitute a fundamental part of healthy diets for people worldwide. In 2022, the number of people facing hunger globally was estimated to be between 691 and 783 million. Food insecurity currently affects 900 million people globally. By 2050, with population growth, we will have 2 billion more inhabitants worldwide, especially in developing countries [8].

In this sense, cattle production in Brazil is relevant for subsidizing protein, both in the domestic and global markets, and for the economy of this country. In the ABIEC's annual report in 2018, Brazilian livestock farming was responsible for generating wealth of R$ 597.22 billion, representing an 8.3% growth compared to 2017. Furthermore, according to the same report, the movement of the beef cattle agribusiness, in 2018, spent a total of R$ 66.17 billion on inputs and services for production, with a total revenue in livestock of R$ 104 billion [6].

The data from the Ministry of Agriculture, Livestock, and Supply, which indicated that the agribusiness GDP was responsible for 26.6% of the Gross Domestic Product (GDP) in 2020, with a 2.0% growth in the agricultural GDP, encompassing the entire production chain (inputs, agriculture, industry, and services). Because of this, growth projections for this market are promising. The United States Department of Agriculture [15] projects a 2.0% increase in beef exports and ranks Brazil as the top beef exporter until 2024, with 455 thousand head of cattle of total exports.

The activity of livestock farming is of importance to the economy of many Brazilian states. In comparison between 2021 and 2020, there was a growth of 3.1%in the Brazilian cattle herd [5]. This scenario of production increase has placed Brazil among the 4 largest beef cattle producers in the world. Furthermore, according to the IBGE, Brazil had 202.78 million cattle in 2020, of which 42.31 million were slaughtered [7].

In the last ten years, considering the largest beef producers in the world, it was precisely in Brazil where production grew the most – an increase of 1.7 million tons in this period. The United States came in second, with an increase of 1.05 million TEC in its beef production over the same period. However, it is in exports that Brazil stands out the most. It is the largest exporter of beef in the world, with 27.7% of global exports in 2022 [7].

Considering this scenario of expansion and valorization of agribusiness, investing in technologies for cattle control and tracking, meeting international export criteria, expanding the market, and boosting the economy of this sector will bring increased profits and reduced losses in the production and development of these animals.

Therefore, the analysis of the aforementioned data is relevant to understand the importance of developing a method based on computer vision with the aim of individually identifying cattle. The purpose of individual identification is to enable tracking and recording of the data history related to the sanitary management of each animal, from birth to slaughter, and conse-

quently, to meet the traceability requirements demanded by importing markets, as well as to cater to more demanding market niches concerned with the certification of beef origin.
In summary, this experiment represents a contribution to the agricultural sector, providing a proposal for an innovative solution for tracking and individual identification of Nelore cattle. With the potential to enhance herd management, optimize animal monitoring, and meet the requirements of international markets, this research demonstrates how the integration of advanced technologies can drive the sustainable development of livestock farming.

2. Related Works

The literature review in this research addresses various aspects related to plant recognition, and identification and tracking of cattle and sheep, highlighting the importance of using advanced technologies such as computer vision and machine learning to enhance herd management. Additionally, it explores the applications of these technologies in livestock contexts and emphasizes the importance of traceability to meet the requirements of international markets and ensure the quality of beef.
The study by Bambil et al. [2] focuses on plant species identification using computer vision and machine learning. The results showed that computer vision was efficient in species identification, with an accuracy rate exceeding 93%. Furthermore, algorithms such as SVM, random forest, and deep learning outperformed the performance of AdaBoost. The SVM model, like this work, was the model that achieved the best result.

Regarding the study by Bateni et al. [3], it focuses on visual classification with few samples. They developed a new architecture called "Simple CNAPS" that outperformed the state-of-the-art on image classification datasets with few samples. This is important because it demonstrates that it is possible to achieve significantly better results with fewer parameters, which may have implications for the efficiency of training deep learning models.
Buller et al. [4] discuss animal welfare policies and their sustainability, arguing that such policies can provoke significant changes in understanding and responding to animal welfare. Although the study does not present experimental results, it highlights the importance of this debate and offers recommendations for sustainable animal welfare policies. While Gong et al. [11] focus on bovine facial recognition and introduce a model based on SK-ResNet that achieved exceptionally high accuracy rates. This is crucial for the practical application of animal facial recognition technology in cattle farming, improving cattle monitoring and management.
In their work, Li et al. [13] present a lightweight model for bovine facial recognition with high accuracy. Additionally, they demonstrated the feasibility of the model by transplanting it to a Raspberry Pi device, reducing computational cost. This has practical implications for implementing facial recognition systems on cattle farms. On the other hand, Santos [14] focus on cattle brand recognition using convolutional neural networks and support vector machines. The results showed that the CNN method outperformed the Bag-of-Features method in accuracy and speed, being relevant for cattle identification and tracking, improving herd management.
Finally, Bakhshayeshi et al. [1] demonstrated that the training capac-

ity of AI may not depend solely on the quantity of photos collected during deployment, but also highlights the effective use of algorithms used in this work, such as those from the YOLO family, to identify and crop the image in real-time, obtaining results showing that with only 20 images per bovine, the model achieves 95.13% accuracy. In summary, these studies demonstrate the effectiveness of computer vision techniques, machine learning, and neural networks in various applications, from plant species identification to animal facial recognition and phenotypic analysis of cattle breeds. Additionally, they highlight the importance of sustainability and animal welfare in modern agricultural practices.

3. Materials and Methods

The collection of images of Nelore cattle faces was carried out in the municipality of Campo Grande, in the state of Mato Grosso do Sul. At the facilities of Embrapa Gado de Corte - CNPGC, the faces of 47 Nelore breed animals were filmed by a GoPro5 camera fixed on a tripod on the side of the containment and weighing chute. A total of 20 calves and 27 females were filmed, resulting in approximately 200 hours of videos from which 2,210 frames were extracted for analysis. With these, detection was performed using the Label-me software, and only the portion of the animals' faces was marked (Figure 1).

3.1. Segmentation

Automatic image segmentation was performed using pre-trained models of the YOLOv8 architecture, developed and provided by Ultraytics. The pre-trained YOLOv8 models are based on the COCO (Common Objects in

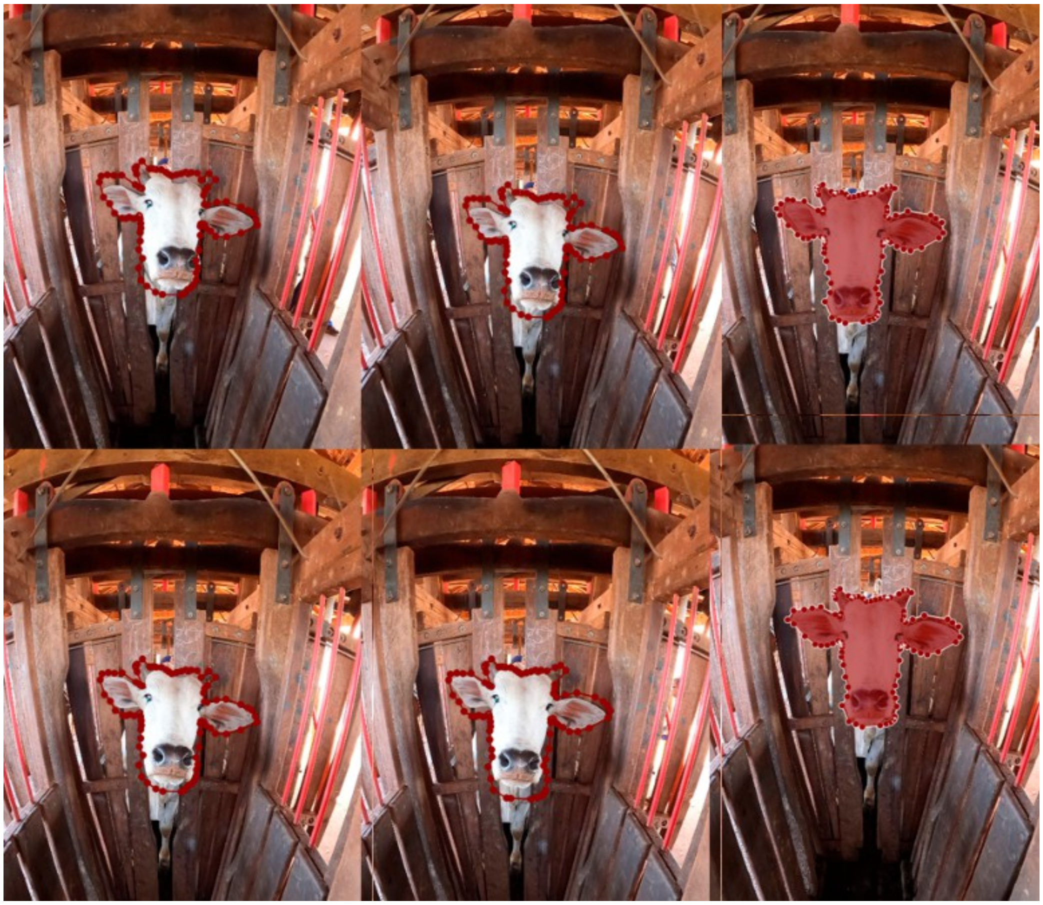

Figure 1: Example of facial segmentation of the animals.

Context) dataset, which encompasses a collection of over 330,000 images. The YOLOv8m-seg model has a configuration default image size configuration of 640x640 pixels, mAP 50-95 box of 49.9, mAP 50-95 mask of 40.8, A100 ONNX speed of 317 ms and A100 TensorRT of 2.18 ms, still contact with 27.3 thousand parameters, resulting in a balance between simplicity and complexity, making it a suitable basis for the development of our own bovine facial segmentation model. For network training, 100 epochs and standard

architecture hyperparameters were used.
The training of the bovine facial segmentation model was conducted through the KeroW platform, which subsequently provided the most efficient training model for this experiment. The YOLOv8n-seg model is the simplest and fastest model; however, it has the worst performance in terms of accuracy. It is suitable for applications where speed is more important than accuracy. The YOLOv8s-seg model is an intermediate model in terms of simplicity, speed, and accuracy. It is suitable for applications where a balance between these factors is required. The YOLOv8m-seg model is the most complex model but also has the best performance in terms of accuracy. It is suitable for applications where accuracy is more important than speed. The YOLOv8l-seg model is the most complex and slowest model but also has the best performance in terms of accuracy. It is suitable for applications where accuracy is very important, and speed is not a critical factor.

3.2. Embedding

After the segmentation step, the images were subjected to a feature extraction process using the Orange software. The relevant features of the images were extracted using the Inception neural network (Figure 2).
The use of the Inception network [12] for embedding extraction is justified by its ability to capture complex and hierarchical information in images. The Inception network, with its diverse architecture of convolutions, is capable of extracting meaningful representations of image features, making it a suitable choice for this context, as it has been applied in bovine recognition [10, 16]. The aim of this step is to capture the essential and semantic characteristics of the object in a vector space, preserving relationships between them. This

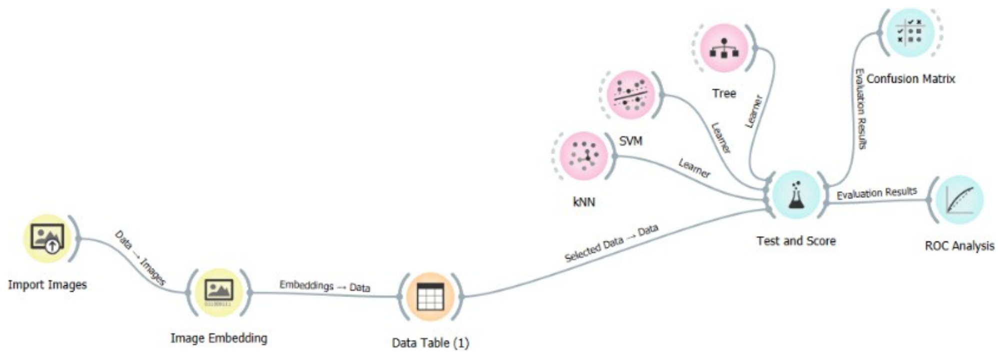

Figure 2: Workflow of the Inception embedding extraction and algorithm testing process.

technique is widely used in machine learning and data mining to enhance the efficiency of algorithms by transforming complex data into formats more suitable for quantitative and computational analyses. This allows the distinctive features of each bovine face to be effectively captured and encoded. The resulting embeddings were subsequently used as inputs for machine learning algorithm analyses.

3.3. Machine Learning and Metrics

In the training process of the machine learning algorithms, the strategy of stratified 10-fold cross-validation was adopted. This approach is widely recognized for its ability to assess the robustness and performance of models while controlling the risk of bias in result evaluation. The cross-validation process was conducted on 10 stratified partitions of the dataset, ensuring that each partition preserved the proportion of different classes consistently. Three machine learning algorithms were used for testing: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Decision Tree

(TREE), all with the default settings of the Orange software [9]. The choice of these algorithms was based on the diversification of modeling approaches and also on other precision livestock farming articles. Each algorithm has its own characteristics, advantages, and challenges.

To compare and evaluate the models, accuracy was measured from a confusion matrix, and the overall performance of the model (AUC) was assessed, which indicates how accurate the probabilities will be. The AUC curve is a comprehensive metric that evaluates the performance of a model at different thresholds and is particularly useful for unbalanced classes.

Additionally, the F1-score metric was used, which is a measure of precision that takes into account both precision and recall, with the goal of correctly classifying instances as positive or negative. The F1 metric balances precision and recall; however, it should not be used in isolation as it does not consider true negatives. Because it is a simple metric, the F1 should be used with caution, especially for unbalanced classes.

Also presented is the confusion matrix, aimed at better understanding the dataset and the hits and misses the algorithm encounters, providing a graphical comparison showing which algorithm or technique was more accurate. Precision will yield misleading results if the dataset is unbalanced; that is, when the number of observations in different classes varies greatly.

4. Results and Discussion

The comparative analysis among the three models shows that the SVM model was the most efficient, with the most accurate and robust algorithm for the dataset in this study. The KNN model is also efficient but not as

Model	AUC	CA	F1	Prec	Recall	MCC
kNN	0,991	0,949	0,949	**0,952**	0,949	0,948
SVM	0,999	0,987	0,987	**0,987**	0,987	0,987
Tree	0,822	0,626	0,627	**0,635**	0,626	0,616

Table 1: Metrics extracted from the results of each of the machine learning algorithms.

precise as the SVM model. The TREE model is the least accurate and robust algorithm among the three models and therefore not a good choice for this dataset.

The results in Table 4 show the metrics of the selected models. The metrics of Precision, Recall, and MCC will not be used in this study since Accuracy, AUC, and F1 represent all other metrics. Analyzing these metrics, we can observe a higher number of AUC, accuracy, and F1 in the SVM model, which is why it was selected as the best model for further study.

Actual \ Predicted	1	19	20	21	22	23	24	25	26	27	28	29	30	Σ
1	21	0	0	0	0	0	0	0	0	0	0	0	0	22
19	0	45	0	0	0	0	0	0	0	0	0	0	0	46
20	0	0	51	0	0	0	0	0	0	0	0	0	0	51
21	0	0	0	54	0	0	0	0	0	0	0	0	0	56
22	0	0	0	0	51	0	0	0	1	0	0	0	0	52
23	0	0	0	0	0	64	0	0	0	0	0	0	0	64
24	0	0	0	0	0	1	43	1	0	0	0	0	0	45
25	0	0	0	0	0	0	1	59	0	0	0	0	0	61
26	0	0	0	0	1	0	0	1	31	0	0	0	0	33
27	0	0	0	0	0	0	0	0	0	35	0	0	0	35
28	0	0	0	0	0	0	0	0	0	0	55	0	0	55
29	0	0	0	0	0	0	0	0	0	0	0	48	0	48
30	0	0	0	0	0	0	0	1	1	0	0	0	53	55
Σ	21	46	51	54	53	65	44	65	33	35	55	48	53	2.210

Figure 3: Confusion matrix for the SVM algorithm

From these graphs, we can observe that KNN and TREE had accuracies of 94.7% and 93.5%, respectively, meaning they predicted this indicated per-

Actual \ Predicted	1	6	7	8	9	10	11	12	13	14	41	42	43	∑
1	19	0	0	0	0	0	0	0	0	0	0	0	0	22
6	0	29	0	0	0	0	0	0	0	0	0	0	0	29
7	0	0	38	0	0	0	0	0	0	0	0	0	0	38
8	0	0	0	28	0	0	0	0	0	0	0	0	0	28
9	0	0	0	0	18	0	4	0	0	0	0	0	0	22
10	0	0	0	0	0	35	0	0	0	0	0	0	0	35
11	0	0	0	0	0	0	42	0	0	0	0	0	0	42
12	0	0	0	0	0	0	0	14	0	0	0	0	0	14
13	0	0	1	0	0	1	0	0	15	0	0	0	0	17
14	0	0	0	0	0	0	0	0	0	25	0	0	0	26
41	0	0	0	0	0	0	0	0	0	0	38	0	0	40
42	0	0	0	0	0	0	0	0	0	0	0	38	0	38
∑	19	29	40	28	18	36	46	14	15	25	44	40	40	2.210

Figure 4: Confusion matrix for the KNN algorithm

Actual \ Predicted	1	2	3	4	5	6	7	8	9	10	46	47	∑
1	16	1	2	1	0	0	0	0	0	0	1	0	22
2	0	10	0	0	0	0	0	0	0	0	0	0	10
3	2	2	118	8	2	0	2	1	0	1	3	0	145
4	0	1	10	90	0	0	4	0	0	3	1	1	120
5	0	0	0	0	95	0	0	1	1	0	1	1	110
6	0	0	0	2	2	9	0	0	0	0	0	0	29
7	1	0	3	7	0	0	18	0	0	1	0	0	38
8	2	0	0	0	1	0	0	21	0	0	0	0	28
9	0	0	0	0	0	2	0	0	10	0	0	0	22
10	0	0	2	2	0	0	0	0	0	25	1	0	35
46	1	0	1	1	1	0	1	0	0	0	26	1	50
47	0	0	1	1	0	0	0	0	0	0	4	17	30
∑	26	16	154	134	115	35	32	25	29	37	50	36	2.210

Figure 5: MConfusion matrix for the Decision Tree algorithm

centage of test instances correctly. Meanwhile, SVM achieved an accuracy of 94.1%, predicting a higher number of correct outcomes in our test instances. The results in Table 1 show that the SVM model performed the best based on the precision metric, followed by the KNN model and finally the TREE model. The SVM model had the highest area under the curve (AUC), the highest accuracy (CA), the highest F1-score, and the highest recall. The KNN model had performance close to the SVM model but not as effective. The TREE model, on the other hand, had the worst performance, with significantly lower AUC, CA, F1-score, precision, and recall compared to the other two models.

Regarding the confusion matrices presented in Figures 3, 4, and 5, we can evaluate the incorrect classifications and deduce that KNN was slightly better with fewer incorrect classifications. Overall, the results indicate that all three models are capable of accurately predicting test instances. However, some recurring confusions can be noticed in each case, as indicated by the compositions of results from SVM (Figure 6), KNN (Figure 7), and TREE (Figure 8). In all three cases, image A represents a correctly classified image and another example of its class, image B shows an individual classified incorrectly, and image C represents the class that was confused with the true class in image B.

For the SVM case, it is noticeable that there was confusion with animals from class 24, as shown in image A of the composition, with class 23 presented in image C. This confusion was also present in KNN, with some animals from class 13 being indicated as belonging to class 07. The same occurred for the TREE algorithm, but with individuals from class 04 being marked as members of class 10.

Figure 6: Composition of results in image form for the SVM algorithm.

Similarly to Bambil et al. [2], who reported plant species identification

Figure 7: Composition of results in image form for the KNN algorithm.

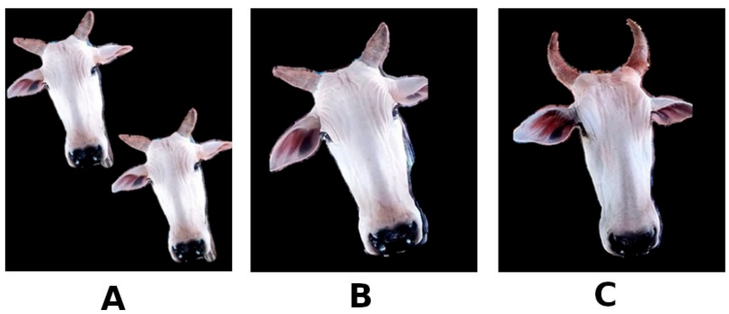

Figure 8: Composition of results in image form for the Decision Tree algorithm.

using computer vision and machine learning, our results showed that algorithms such as SVM and random forest outperformed the AdaBoost, aligning with the objectives of this experiment. Our findings corroborate with Gong et al. [11], who focused on facial recognition of sheep and introduced a model based on ResNet-50 that achieved high precision rates. Despite achieving good results, Santos [14] focused on cattle branding recognition using convolutional neural networks and support vector machines. Their results showed that the CNN method outperformed the Bag-of-Features method in precision and speed, being relevant for cattle identification and tracking, thus improving herd management.

However, it is known that the problem is highly complex in terms of generalization and still requires further investigation, particularly due to the lack of high-performance software for this application on the market. Recently, Bakhshayeshi et al. [1] published a summary indicating a potential direction for continuing the experiment we reported, as, despite the large number of images, generalization remains limited by the small number of animals. Therefore, a direct recommendation to address this issue would be to focus on constructing an image database with a wide diversity of individuals, in order to enhance generalization capability. Finally, the correlation between the presented studies and the experiment conducted highlights the growing importance of computer vision, machine learning, and neural network technologies across various applications, ranging from plant species identification to animal facial recognition.

5. Conclusion

The use of Computer Vision and Machine Learning applied to a set of previously segmented images proved to be relevant for the facial recognition of Nelore cattle. It is recommended that future work replicate the experiment using other AI technologies and tools for facial recognition, such as the Few-shot Learning technique, which involves training models with minimal data.

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CRediT author statement

Pietro Claure: Conceptualization, Investigation, Methodology, Writing – Original draft. **João Porto**: Conceptualization, Formal analysis, Software, Writing – Review & Editing. **Andre Simões**: Data curation, Validation. **Alexandre Bezerra**: Investigation, Validation. **Fabrício Weber**: Software, Data curation, Funding acquisition, Supervision. **Adair Junior**: Software, Funding acquisition, Visualization. **Pedro de Moraes**: Methodology, Visualization. **Rodrigo Antunes**: Data curation, Investigation. **Urbano Abreu**: Supervision, Project administration. **Vanessa Weber**: Supervision, Funding acquisition, Resources, Project administration.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT[1] and DeepL[2] in order to improve the translation to english language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

[1]https://chatgpt.com/
[2]https://www.deepl.com/

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