Convolutional neural networks for the prediction of cattle age using x-ray images of skulls

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Introduction: Cattle dentition evaluation is commonly used as an age indicator when birth records are not available. The visual method uses eruption and attrition of incisors [1] to segregate carcasses under (UTM) from over (OTM) 30 mo of age. The ability to recognize and classify image patterns using deep learning algorithms, in particular convolutional neural networks (CNN), is becoming a methodology of choice for analyzing images [2].The present study aimed to evaluate the potential of using x-ray images of beef skulls and CNN to classify carcasses as either UTM or OTM of age.

Material and methods: X-ray images were collected from 139 skulls from animals of known birthdates within a wide range of ages and sex: youthful animals (UTM, heifers and steers n=115, 13.7-24.8 mo) and mature animals (OTM, cows, n=24, 33.6-153.6 mo). Dorso-ventral mandibular x-ray scans were taken using a high quality digital hand held mobile x-ray system (XPrime. Vet 20-BT, POSKOM, Korea). Images were pre-processed for the development and training of CNN models. A data augmentation procedure was applied to improve model generalization capabilities, and a loss function class weight setting was used to avoid having the algorithm default to the class with higher proportion of observations. The best two CNN models were validated using an independent population of 84 skulls (12 OTM and 72 UTM).

Results: In a preliminary screening of CNN model architectures [3], 10 model architectures were generated by adding/modifying building blocks to create new models and train them from scratch, and/or use Transfer Learning [4]. Two of the models evaluated showed potential in terms of training and external test performance. A maximum of 5 and 7 blocks of trainable convolutional layers were set for models 1 and 2, respectively. In both models, a number of dense, batch Normalization, activation and dropout layers (top layers) were added for classification. At the end of the sequence of layers, a final dense layer was also added (output layer). The number of trainable, top layers and hyperparameters were tuned to find the best model architecture and configuration using an optimization method. Model 1 was based on Transfer Learning using the VGG16 model, and pre-trained on the Imagenet [4]. This model was 94% accurate for prediction of the training set classes and 100% accurate for classifying OTM and UTM animals from the test set. Model 2 was based on several basic naïve models [5] and reached an accuracy of 88% for the training set and 93% for the test set.

Conclusion: The results of this exploratory study suggest that carcass age segregation (OTM/ UTM) is feasible using CNN procedures on x-ray images from beef skulls. The present study may be improved by providing a larger training set, particularly increasing the number of carcasses from animals close to the 30 mo of age break point, and by optimizing hyperparameters of the model (e.g. learning rate, batch size, or number of iterations). Similarly, changing the number of hidden layers and the types of layers (e.g. convolutional, pooling and fully connected) may improve the prediction accuracy.

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