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Application of Machine Learning Identification and Classification of Muturu and Keteku Cattle Species for a Smart Agricultural Practice in Developing Countries such as Nigeria

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ABSTRACT: Smart technologies have drastically reshaped the traditional methods of practicing agriculture as witnessed in husbandry. In this paper, a novel application of machine learning identification and classification of Muturu and Keteku cattle species in Nigeria was proposed as the mainstream model that enables the precision and intelligence perception of animal husbandry for a smart agricultural practice using enhanced mask region-based convolutional neural networks (mask R-CNN). A performance accuracy of 0.92 mAP (mean Average Precision) was achieved by the enhanced mask R-CNN model, making it on a par with the existing models.

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Smart agriculture has the enablement to analyze individual objects in its domain such as animal husbandry by using plenty of data acquired via sensors, and perception tools precisely residing in its core (Bello *et al*., 2022). One of the aims of smart animal husbandry is to improve the identification and classification methods of individual animals for their welfare monitoring, robust dairy and beef production, and for an overall productive animal farming which is the main focus of this paper. Based on these assertions, this paper proposed mainstream model that enables precision and intelligence perception for a smart agricultural practice. The widely acceptability of convolution neural network-based methods with ability to achieve accurate result-oriented image feature extraction and representation has continue to grow in the field of vision and image processing (Bello *et al*., 2021a; Bello *et al*., 2021b; Bello *et al*., 2021c). Although, these methods have been widely applied for animal identification purposes such as cattle without the need for pre-specifying any features (Kumar *et al*., 2018) but, the application of CNN-based methods in monitoring the activities of animals in animal farming is still not widespread (Li *et al*., 2021). Simonyan and Zisserman (2014) proposed the two-stream network, which is one of the tracking models that exist in literature for tracking objects in motion. To capture relevant information on object from still frames and track the movement of the object between frames, the two-stream network makes use of several layers of CNNs and optical flow CNN. Long-term Recurrent Convolutional Networks (LRCNs) (Donahue *et al*., 2015) were developed shortly after two-stream network was proposed. LRCNs generally consist of several CNNs, namely ResNet, Inception modules, Xception and VGG for extracting temporal features and spatial features. Because the architectures of LRCN are practical for tracking performance, it is the most applied tracking model. Generic Object Tracking Using Regression Networks (GOTURN) (Held *et al*., 2016) is a lightweight network model with 100 fps (frames per second) achievement for object tracking. The datasets for initial training of GOTURN were filled with generic objects. During the testing of the

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trained network, region of interests (ROI) on the frames are employed as input data, making the continuous prediction of the location of target possible. Slow pathway and high pathway are the two streams of frames used by the Slow Fast network (Feichtenhofer *et al*., 2019) to track objects. Hungarian Algorithm (HA), Simple Online and Real-time Tracking (SORT), Spatial-aware Temporal Response Filter (STRF), Channel and Spatial Reliability Discriminative Correlation Filter tracker (CSRDCF) and Munkres Variant of the Hungarian Assignment Algorithm (MVHAA) are other algorithms developed for animal tracking and monitoring (Alameer *et al*., 2020; Chen *et al*., 2020; Cowton *et al*., 2019; Zhang *et al*., 2019). Among the object detection models that utilized these algorithms to detect and track animals in images are SSD, VGG, Faster R-CNN, FCN and YOLO (Li *et al*., 2021). They do the detection and tracking by using the geometric features of the animals in images in continuous frames. Ren *et al*. (2021) presented an ultra-wideband technology based tracking system as a method that is reliable and efficient enough for monitoring cattle behavior. Their work bears a resemblance to the work of Salau *et al*. (2019) who presented dairy cows' contact networks derived from videos of eight cameras. Computer vision module was employed by them to analyze and detect positive social behavior interactions and negative social behavior interactions in term of feeding among individual cattle in the experiment on foreground video stream using Long-term Recurrent Convolution Networks (LRCNs) model. Seven dairy cattle in the feeding area were employed for the system implementation and testing performance. The ultra-wideband technology based tracking system recorded accuracy with mean error and standard deviation of 0.39m and 0.62m respectively. 93.2% was recorded as detection accuracy for social interactions experiment. If individual cattle are in close body contact, the detection accuracy of the Real-time Locating System (RTLS) is not sufficient for the identification task. Hence, the objective of this work is to propose a mainstream model for application of machine learning identification and classification of Muturu and Keteku cattle species in Nigeria to assist the precision and intelligence perception of animal husbandry for a smart agricultural practice using enhanced mask region-based convolutional neural networks (mask R-CNN).

MATERIALS AND METHODS

A group of cattle in a ranch was employed for the identification and classification of individual cattle using their body patterns and instance segmentation (mask) method. The species of the cattle used for the experiment are Muturu and Keteku cattle species. For the body patterns identification, neural networks with convolutional layers were used. Classification of individual cattle using instance segmentation was by using enhanced mask R-CNN (Bello *et al*., 2021b). The essence of these approaches is to mitigate the challenges of using the traditional cattle identification and classification methods which most of the time cause injury and even the death of the animal. Average precision (AP) and mean average precision (mAP) were used as the metric for evaluating the performance of the enhanced mask R-CNN model as given below

$$\mathrm{AP} = \sum\nolimits_{n=1}^{N} [R(n) - R(n-1)] \cdot \max P(n) \tag{1}$$

$$\mathrm{mAP} = \frac{1}{n} \sum\nolimits_{n=1}^{n} AP_i \tag{2}$$

$$\mathrm{IOU} = \frac{A \cap B}{A \cup B} \tag{3}$$

Equation (1) represents average precision (AP) where N is the calculated number of precision-recall (PR) points produced. $P(n)$ and $R(n)$ are the precision and recall with the lowest n-th recall, respectively. Equation (2) is the mean average precision (mAP) where, APi is the AP of class i, and n is the number of classes. Equation (3) is the intersection over union (IOU) that defines the extent of overlap between the predicted and ground-truth bounding boxes; A and B are the bounding boxes of the predicted objects and their ground truth respectively.

The experiment was implemented using the following software; Operating System: 64 bits Windows 10, IDE: Visual Studio 2019, Python library: Keras and MATLAB: R2020b, and the following hardware; CPU: Intel Core i5 processor@2.4GHHz, RAM: 16 Gigabytes, Graphic card: GeForce GTX 1080 Ti, Hard-disk: 2 Terabytes.

RESULTS AND DISCUSSION

Fig. 1 and Fig. 2 show the visual results of the research experiment carried out on the cattle. The main purpose of convolutional neural networks is to train and test each input image that passes through it, with the convolution primarily conserving the bond that exists between the pixels. The quantitative evaluation result of model 1 for cattle identification carried out on the training and testing data is shown in Table 1. Table 2 shows the quantitative evaluation result of the enhanced mask R-CNN (model 2) for cattle classification.

Table 1. Accuracy of model 1 for cattle identification

Dataset (images)	Accuracy (%)
Training data (600)	92.59
Testing data (400)	89.95

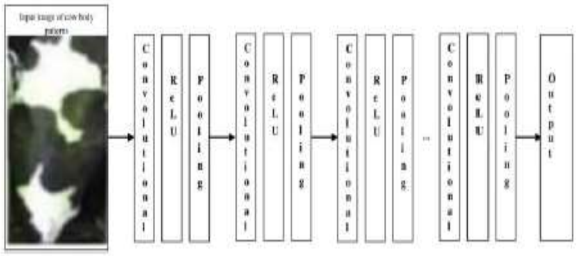

Fig. 1. Convolutional neural network layers of model 1 for cattle identification

Table 2. Accuracy of model 2 for cattle classification

Cattle breed (dataset)	Metric	AP at 0.50 IOU
Keteku	AP	0.91
Muturu	AP	0.92
	mAP	**0.92**

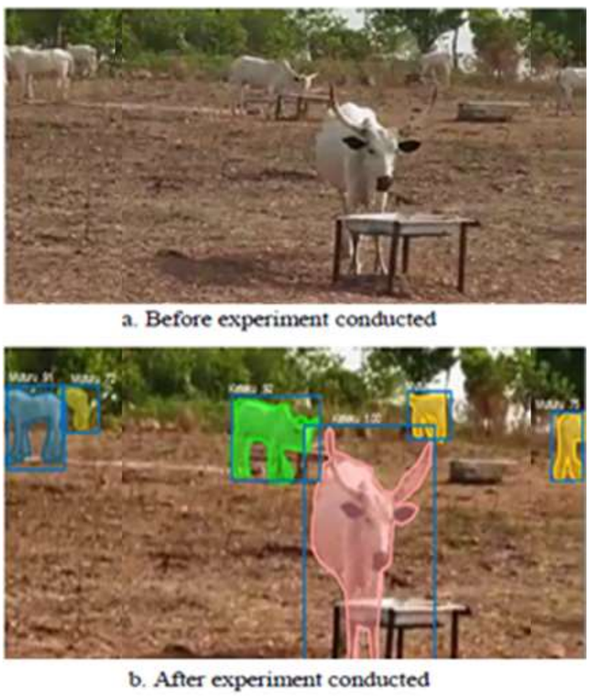

Fig. 2. (a) Before experiment carried out and (b) after experiment carried out for cattle classification using enhanced mask R-CNN

The evaluation results of the neural networks with convolutional layers (model 1) and enhanced mask R-CNN (model 2) have been presented. The results show great performance for object identification and classification compared to the models aforementioned in the literature. As mentioned earlier, the enhanced mask R-CNN was implemented on 64 bits Windows 10 Operating System with visual studio 2019 IDE, Keras Python library and R2020b MATLAB. For utmost compatibility performance, Intel Core i5 processor@2.4GHHz CPU, 16 Gigabytes RAM, GeForce GTX 1080 Ti Graphic card, and 2 Terabytes hard-disk were employed as the hardware specifications. Moreover, with the integration of these system specifications and utilization of the proposed model, the limitations such as color misjudgment of feature descriptor in the existing methods were overcome making identification and classification of Muturu and Keteku cattle species possible as shown in Fig. 2. In addition, close body contact does not affect the detection accuracy in our proposed method unlike what is obtained in Ren *et al*. (2021) in which if individual cattle are in close body contact, the detection accuracy of the Real-time Locating System (RTLS) will be insufficient for the identification task.

Conclusion: Proposed in this paper is a mainstream model for application of machine learning identification and classification of Muturu and Keteku cattle species in Nigeria to assist the precision and intelligence perception of animal husbandry for a smart agricultural practice. To achieve on a par with the existing models in identifying and classifying the cattle species, the fully connected layers (FCL) of the existing mask R-CNN were enhanced. Our future work seeks to improve on the proposed model for the identification and classification of species of different animals.

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