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# Identification of animal individuals using deep learning: A case study of giant panda

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ABSTRACT

Giant panda (*Ailuropoda melanoleuca*) is an iconic species of conservation. However, long-term monitoring of wild giant pandas has been a challenge, largely due to the lack of appropriate method for the identification of target panda individuals. Although there are some traditional methods, such as distance-bamboo stem fragments methods, molecular biological method, and manual visual identification, they all have some limitations that can restrict their application. Therefore, it is urgent to explore a reliable and efficient approach to identify giant panda individuals. Here, we applied the deep learning technology and developed a novel face-identification model based on convolutional neural network to identify giant panda individuals. The model was able to identify 95% of giant panda individuals in the validation dataset. In all simulated field situations where the quality of photo data was degraded, the model still accurately identified more than 90% of panda individuals. The identification accuracy of our model is robust to brightness, small rotation, and cleanness of photos, although large rotation angle ($>20°$) of photos has significant influence on the identification accuracy of the model ($P < 0.01$). Our model can be applied in future studies of giant panda such as long-term monitoring, big data analysis for behavior and be adapted for individual identification of other wildlife species.

## 1. Introduction

Most studies on behavior and ecology of wild animals requires that research subjects are individually recognizable (Crouse et al., 2017). Individual identification is not only the essential basis of unbiased data collection (e.g. records of individual behavior data), but the key of accounting for individual variation in variables of interest (e.g. social relationship, special behavior) (Cronin, 2012). For animal populations in short-term studies, the number of individuals is relatively low, researchers often identifying individuals through their natural variation (e.g. difference in body size and shape or presence of injuries and scars). These studies mainly focus on scientific problems over short period of time, such as population size assessment in study area or exploration of social structure (Jackson et al., 2011; Shinde et al., 2004). However, the methods for identifying individuals based on obvious variation of appearance are often infeasible for species with a large population size (e.g. spider, monkey) (Brugière, 2016; Ramos-Fernández and Ayala-Orozco, 2003; Wong and Sicotte, 2010) or without conspicuous difference in characters (e.g. giant panda) (Zheng et al., 2016). Too many individuals mean an increase in the number of individual features to be recorded, while animals without obvious features mean subtle changes in features. Under these circumstances, erroneous identification of individuals often occur (Crouse et al., 2017). Moreover, short-term research is no longer sufficient for current research requirements, long-term data on known individuals is increasingly needed for further studies (Zheng et al., 2016). For example, it's important that establishing a individual identity library for long-lived mammalian species with a complex social structures. Such a database can provide identification and tracking of target individuals and allow researchers to conduct long-term studies (e.g. life history parameters, dynamics of social structure in a population).

Longitudinal research requires long-term track record of behavioral

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and ecological data of research objects, which can be challenging. One of the primary challenges is developing an appropriate method for target individual identification (Bergqvist et al., 2015; Crouse et al., 2017). Current methods used for identity animal individuals can generally be divided into two types. One is invasive method that often involves capturing and tagging. This kind of method often requires research objects be captured via mist netting (for birds) (Fls, 2015), trapping (for some mammals) (Zohdy et al., 2014), even anaesthetic rifle (for large mammals) (Zhang et al., 2015). Researchers then put a unique mark (e.g. identity tag) on captured animals for future identification. The other type of method is non-invasive, such as visual identification, in which researchers rely on their knowledge of variation in appearances to identify individuals. The non-invasive approach, compared to the invasive method, can reduce disturbance to animal and is relatively easier to collect data (Zheng et al., 2016). However, most long-term or large-scale studies need to be done by multiple researchers. Data consistency can be a challenge, due to different identification criteria used by multiple researchers in their research period. For large scale studies involving several small scale research sites, it will be difficult to integrate data from each site (Crouse et al., 2017).

As a flagship species for biodiversity conservation worldwide, the conservation of wild giant panda (*Ailuropoda melanoleuca*) has been of widespread concern. The long-term field tracking and monitoring data for giant pandas is often lacking. One of the main reasons is that there is no proper way to identify and monitor target individuals of giant panda. Past methods for identifying known individuals of giant panda mainly included GPS collar tracking (Zhang et al., 2015; Hull et al., 2016; Zhang et al., 2017), manual visual identification based on experience (Zheng et al., 2016), distance-bamboo stem fragments method and molecular biology method. The service life of GPS collar is about two years, which can limit their applications for long-term tracking. Moreover, this approach is difficult to apply to large numbers of individuals of giant panda in study area due to the high costs associate with collar deployment. Because of the pandas' secretive nature, researchers find it difficult to encounter individuals in the wild, so artificial recognition based on experience has only be used to identify individuals of giant panda in captivity. In addition, the reliability of the methods relying on experience for individual identification is vulnerable to subjective error. The distance-bamboo stem fragments method and molecular biology method were mainly used in the third and fourth population survey of giant panda. The moving distance of each giant panda depends on multiple factors (e.g. reproduction, season, individual size, food availability) and it's difficult to obtain an accurate threshold value (Zhang et al., 2014; Hull et al., 2015; Zhang et al., 2015). Furthermore, the measurement results can be easily influenced by subjective factors (Zhan et al., 2006). Molecular biology method is highly accurate, but it costs a lot of manpower and resources, and fresh feces of giant panda are hard to collect in the field (Shi et al., 2016).

Due to the limitations of existing approaches in identify giant panda individuals for long-term individual monitoring, it is necessary to explore novel techniques for giant panda individual identification. Recently, the artificial intelligence and computer vision provides a powerful tool for the development of new individual identification methods (Youssif and Asker, 2011). These technologies have proven feasible to identify individual animals (Crouse et al., 2017; Freytag et al., 2016; Jin et al., 2019). Although giant pandas lack obvious characteristics for individual identification because their whole body is composed of only black and white fur (Li et al., 2018; Norouzzadeh et al., 2018), image recognition based on deep learning has shown good identification performance in similar circumstances (e.g.,(Freytag et al., 2016)). A more important fact is that image recognition is a non-invasive, low-cost method, the data used to identify individuals are easy to collected and less susceptible to natural factors (e.g. rain, soil matrix, fallen leaves). This approach can be used in field research at a large spatial scale. So this technology has the potential to address the limitations of past methods to identify giant panda individuals.

In this study, we used convolutional neural network under deep learning to develop a new individual identification model for giant panda. To investigate model's performance under various conditions that might degrade the quality of photo data, we set up multiple treatments to simulate photo degradation due to large face angle, low brightness, and high saturation. A large number of facial photos collected from captive giant panda are used to ensure the applicability and reliability of the identification model. This new individual identification model is the first but essential step for studies on wild giant panda that need to identify and track known panda population (e.g. monitoring panda behaviors (e.g. social, foraging)). Our model represents a breakthrough in panda individual identification, which can greatly save labor and time cost to collect long term data on panda individuals for related studies. The approach can also be adapted to meet the needs for individual identification of other wildlife species.

## 2. Materials and methods

### 2.1. Data collection

We collected face images from 25 captive giant pandas located in the Chengdu Research Base of Giant Panda Breeding (6 individuals) and 2 bases of the China Conservation and Research Centre for the Giant Panda (CCRCGP): Dujiangyan (9 individuals) and Wolong (10 individuals). Giant pandas' photos from the Chengdu Research Base of Giant Panda Breeding and the CCRCGP Dujiangyan base were used to train and test the model, and giant panda photos from the CCRCGP Wolong base were used to verify the model's ability to detect unknown individuals. We kept at least 5 m away from the giant pandas to avoid disturbing them when taking photographs. We used the zoom in function of the camera or the phone to acquire photo of the panda face with a photo size roughly equivalent to that achieved when facial features (e.g. eye, ear) were clearly captured by the photographer. In order to enhance the model's ability to recognize different resolution photos, we took photos at resolution of only the face from $120 * 120$ pixels to $600 * 600$ pixels (taken by both mobile phone and camera). We took photos of pandas' faces in a variety of behaviors (e.g. when the giant panda walking, sitting, eating), because we found that multiple facial photos make the recognition model more robust (Cao et al., 2018).

The basic workflow of photo preparation was as follows: volunteers screened the raw images to select photos of each giant panda that had the most facial variety. Another requirement was that the angle of head be up – a downward and/or tilted head of $> 30^{\circ}$ resulted in lower quality photos. Then, we used LabelImg photo tagging software to mark the face of the giant panda and python script to intercept and capture it. Finally, we used Photoshop CS6 along the face to intercept the giant panda's face contours, we adjusted the aspect ratio of images to 1:1 (Fig. 1).

### 2.2. Identification network and improvements

The identification network used in this study was VGGNet. It is a kind of network structure of Convolutional Neural Networks (CNN) under deep learning and was often used to extract image features. In our experiment, the VGGNet consists of 5 convolution modules, 3 fully-connection layers, and a soft-max layer. Each set of convolution modules contained a convolutional layer and a pooling layer. The convolutional layer extracts the features of the input image, and the pooling layer compresses the input image, retaining the main features and simplifying the complexity of network computing. After the convolution and pooling is completed, the extracted features are classified through the full connection layer. Finally, probability mapping is conducted through the soft-max layer, and the category with the largest probability is selected (Simonyan and Zisserman, 2014) (Figs. 1 & 2).

Our training dataset contained multiple facial photos, in order to make the final training model more robust to diverse variety (e.g. facial

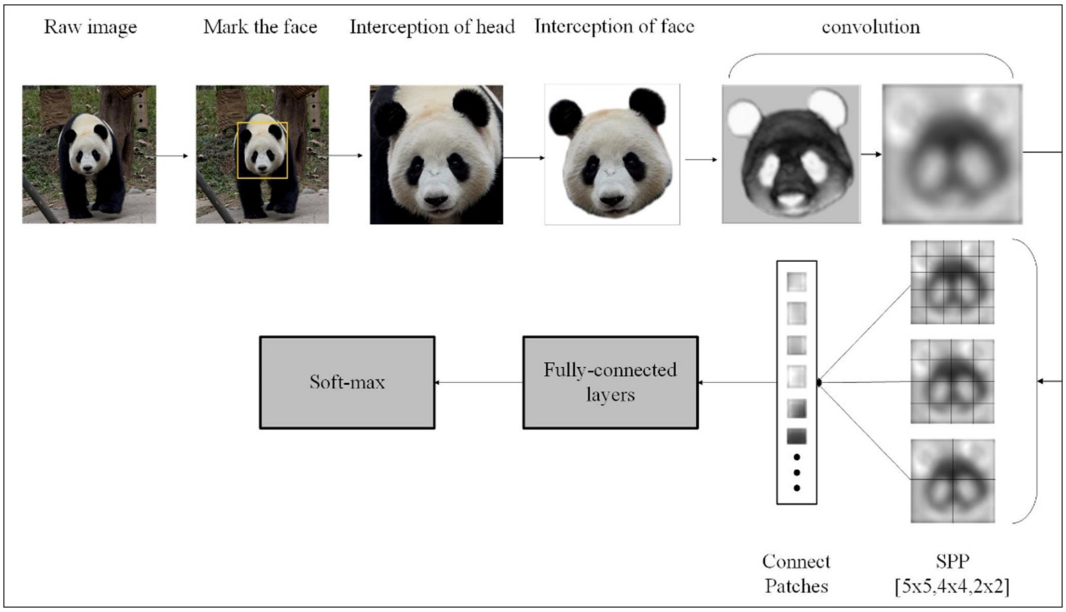


**Fig. 1.** The flow chart of image processing.

photos of eating bamboo). We improved the network and replaced the last pooling layer with a Spatial Pyramid Pooling Layer (SPP). To avoid the Exploding Gradient Problem (EGP) and more easily train the model, we replaced the Dropout layer with a BatchNorm (Batch Normalization) layer (Ioffe and Szegedy, 2015), reducing the number of network layers to 11.

### 2.3. Model training

Our data set included 65,000 face images of giant pandas from the CCRCGP Dujiangyan base and the Chengdu Research Base of Giant Panda Breeding with about 4300 images of each individual. Then, we divided the data set using a 6:3:1 ratio for the training, validation, and calibration of the model. Specifically, the training set (39,000 images) was used for model fitting of the data, the validation set (19,500 images) was used to evaluate the generalization ability of the final model, and the calibration set (6500 images) was used to adjust the hyperparameters of the model and for preliminary assessment of the model's identification accuracy during model training. To consider and enhance the applicability of the model in the field, we made changes to the images, including two hierarchical treatments. The first hierarchical treatment is dirtying and clean (faces of wild giant pandas may be dirty), and the second hierarchical treatments are face rotation (the head angle of wild pandas captured by infrared cameras may not always be ideal) and changes to brightness (light conditions change in the field). Totally, we set two levels for each factor, including clean (no treatment) and dirtying (saturation change from 0.6 to 2.5 with 1 being the standard); rotation 0–20°and rotation 20–45°; brightness increase and brightness decrease (brightness change from 0.7 to 1.3 with 1 being the standard) (Fig. 3). A multi-way ANOVA was used to compare the influence of experimental treatments on the identification accuracy. An independent samples *t*-test was used to compare the difference in the effects of varying saturation on accuracy. The significance level was set as alpha = 0.05.

For model training, we used the Tensorflow toolbox (Google's open source library), and used GPU NVIDIA Quadro P5000 (16GB) for training. To accelerate the convergence of the identification network and solve the problem of the unstable gradient of deep networks, we adopted the Xavier initialization method (Glorot and Bengio, 2010). The initial batch size was set as 128 and the learning rate as 0.001.

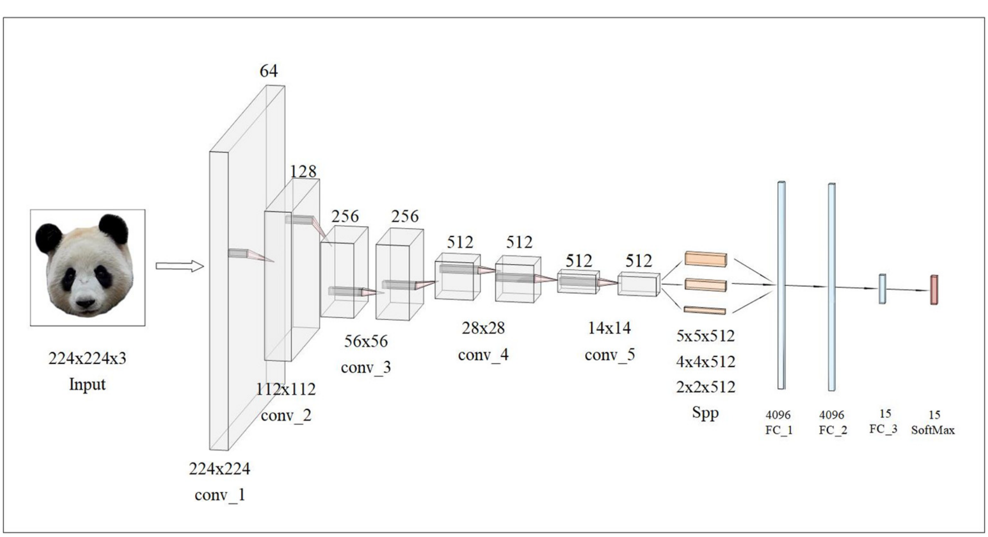


**Fig. 2.** The image classification workflow. Conv_1 to Conv_5 represent convolution module; Spp represents Spatial Pyramid Pooling Layer; FC_1 to FC_3 represent fully-connection layer. The Arabic numerals above each layer (from conv_1 module to conv_5 module) represent the number of channels; the Arabic numerals below each layer (from input module to Spp layer) represent the length and width of the feature map. The 4096 above FC_1 and FC_2 represents the number of neurons. The 15 above FC_3 represents 15 values (15 panda individuals) from FC_2, whichwill be exchanged to 15 probability values and the maximum probability (namely which panda individuals is most likely to be the result of input image) will be selected as result.

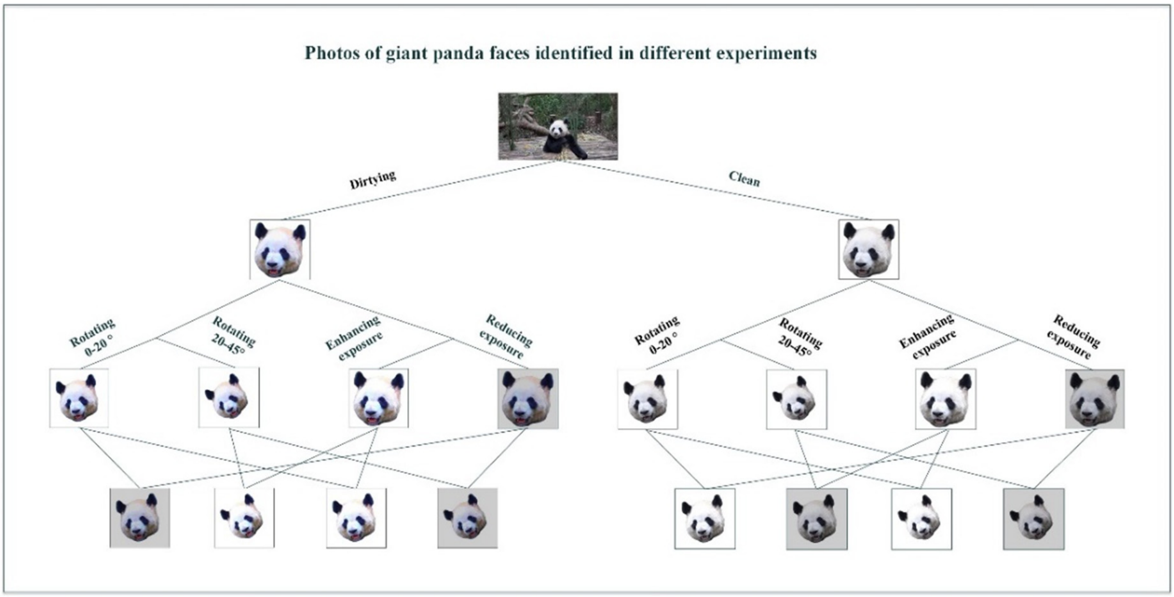


**Fig. 3.** Photos of giant panda faces identified in different conditions.

When the error of the validation set in the training process no longer decreased, we set the learning rate to decrease by a factor of 5 and the total number is set to 3 times. Finally, the training stops after 250,000 iterations (Simonyan and Zisserman, 2014).

### 2.4. Model validation

Our test set included 19,500 facial images of giant pandas collected from the Chengdu Research Base of Giant Panda Breeding and the CCRCGP Dujiangyan base - about 1300 images of each individual. The test set also contained images processed by the different treatments detailed above (Fig. 3). In addition, a total of 3000 images of 10 individuals collected from the CCRCGP Wolong base were used to verify the ability of the model to identify unknown individuals.

## 3. Results

Our model achieved 95.0% accuracy in identifying the general test set. This set contained all of the experimentally processed face images of giant panda in addition to the original test images. In the test of identification of unknown individuals, the mean accuracy was 21.3%, this means that the predicted probability by the model that these 10 individuals within the non-training set individuals is 78.7% (Table 1 in Supporting Information).

In the single factor experiment, the average accuracy of rotating the image 0–20°was 95.0% while the average accuracy of rotating the image 20–45°was 91.1%; the average accuracy of the "dirtying" images was 95.4% and the average accuracy of the "clean" images was 94.4%; the average accuracy of brighter images was 95.1% and the average accuracy of less bright images was 95.2% (Table 2 in Supporting Information). Results of the *t*-test indicated that the accuracy was significantly influenced by rotating the images of giant panda 20–45° ($P < 0.01$), but rotating 0–20°, brightness change did not significantly affect recognition rate (Table 6 in Supporting Information).

In the two factors combination experiments, the average accuracy of increasing brightness + rotating the image 0–20° was 93.9%; the average accuracy of decreasing brightness + rotating the image 0–20° was 95.6%; the average accuracy of increasing brightness + rotating the image 20–45° was 91.3%; the average accuracy of decreasing brightness + rotating the image 20–45° was 92.1%. The average accuracy of increasing brightness + dirtying was 95.2%; The average accuracy of decreasing brightness + dirtying was 95.2%; The average accuracy of rotating 0–20° + dirtying was 94.8%; The average accuracy of rotating 20–45° + dirtying was 91.9% (Tables 3 & 4 in Supporting Information). Results of the multi-way ANOVA indicated that the interaction of brightness change and angle of rotation had no significant effect on accuracy (Table 6 in Supporting Information).

In the three factors combination experiments, the average accuracy of increasing brightness + dirtying + rotating 0–20° was 94.7%; The average accuracy of decreasing brightness + dirtying + rotating 0–20° was 95.7%; The average accuracy of increasing brightness + dirtying + rotating 20–45° was 90.8%; The average accuracy of decreasing brightness + dirtying + rotating 20–45° was 91.2% (Table 5 in Supporting Information). Multi-way ANOVA results show that interaction effects among multiple treatments did not significantly affect recognition rate, which suggested that our model has good effect in the identification of such images, but the recognition rate of the image containing rotating processing of 20–45°was generally lower than that of the image without processing of rotating 20–45° (Table 6 in Supporting Information).

To understand where this model was erring, we further explored the false outputs. Using the method proposed by Schofield et al. (2019), we created a confusion matrix of the 15 individuals in the test set (Schofield et al., 2019). This model was more accurate at identifying certain individuals with images photographed from multiple directions. The lowest accuracies are individual 5 and 9 (Fig. 4 in Supporting Information).

## 4. Discussion

It has been increasingly recognized that it is important to develop an accurate, reliable and low-cost method for giant panda individual identification. Our identification approach can achieve a 95% accuracy in the identification of giant panda individuals based solely on facial images. In all experiments that simulated field situations that might lead to low photo quality, this identification model still achieved a high identification accuracy (over 90% in all experiments). This high accuracy was due to that we have improved the identification network and the fact that we collected as much data as possible to represent the great variation in panda facial features. This model can not only greatly enhance giant panda individual monitoring and long-term big data analysis of wild giant panda based on images or video (e.g. data from infrared cameras), but also can promote the study of life history and social mechanism of wild giant pandas. Additionally, this study examined the ability of the model to identify non-dataset individuals, our results show that the model can identify individuals that are not from dataset with fair accuracy (78.7%), suggesting our model has potential to help researchers determine whether the individual in the data is within the target population.

For real-world implementation, it's essential to establish an identity database. The steps include data collection, data pre-processing and artificial classification. The data can come from infrared cameras or network monitoring, which have been widely used in animal conservation studies. We found that large rotation angles in the images significantly reduced the identification accuracy. We therefore recommend that cameras should be set up along animal trails and at a height similar to that of animal's head. We also found that the more pixels present in an image, the easier it was to identify individuals, which is consistent with the finding of previous study (i.e., (Lui et al., 2009)). Researchers should thus choose infrared cameras with high resolution and select their locations so that the shooting distances are more likely to be within 2 m. To collect as much available data as possible, researchers should install infrared cameras according to specific characteristics of target species. For example, researchers can choose body as focus of shooting if species with distinguishable coat pattern. During data processing, the training set should choose images with multiple poses, high resolution, different environments, brightness, and activity. The optimal aspect ratio of image data used in neural network training is 1:1 at the present stage (Simonyan and Zisserman, 2014), but there are some images that are not 1:1 after interception and the stretching and compression of the image can cause distortion and alter the aspect ratio. Therefore, it is necessary to preprocess the data early in the protocols, which can be solved through two methods: one is to crop the photos, and the other is to add edges to the photos, which can be selected according to specific needs. After data pre-processing, one of the most important things for researchers is to make a preliminary distinction between pandas based on their facial features according to a systematic and hierarchical approach (Zheng et al., 2016), which will generate a basic dataset. Additionally, researchers can adopt the method of identifying unknown individuals through our model to further classify individuals that cannot be identified artificially in previous step. Then the panda identity database can be established. Finally, researchers train the model of individual identification based on this identity database. If a gradient explosion problem occurs during model training, this problem can be solved through reducing the learning rate and the number of layers of the identification network.

The time consumption of training and testing depends on computer configuration and data volume.For our case, it took about 7 h. However, we organized five volunteers and spent about a week for manual processing of face segmentation. Deep learning approach might be developed to perform initial segmentation of panda face to reduce the implementation time. This task is challenging and requires a lot of time and effort to complete. Generally, object segmentation includes feature extraction and up-sampling. The instance segmentation is suitable for multi-object image segmentation (because images photographed in field may contain more than one individual). Among the many segmentation methods, the U-net may be a reliable network for achieving face segmentation in the future (Ronneberger et al., 2015).

With the widespread use of infrared cameras, it has become an increasingly more powerful tool for global wildlife monitoring (Gálvez et al., 2016). A large number of images of wild animals are being taken, thus providing a great potential for tracking target individuals, and conducting behavior observation of a wide range of species through images. There are many rare and endangered animals in nature, and it's difficult to identify target individuals of many them though traditional methods. Species without obvious facial features (e.g. primates) and without unique coat patterns (e.g. sambar deer) present obstacles in identifying unique individuals (Crouse et al., 2017; Karanth et al., 2014). Our model performs well in the identification of giant panda individuals which lack both expressive faces and unique coat patterns, and it can be adapted to the individual identification of other species. The only requirement for application to other species is to train a unique identification models for those species. Once accurate models are developed, they can be applied to camera trap data across space and time to greatly promote ecological and behavioral research of species of concern (e.g., giant panda) and provide the basis for better conservation and management. The models in this paper are already scripted into a Matlab package, which will enable more ecologists to use this method for individual identification of a wider range of wildlife species under various settings.

## CRediT authorship contribution statement

**Jin Hou**:Investigation, Data curation, Writing - original draft.**Yuxin He**:Methodology, Software.**Hongbo Yang**:Writing - review & editing.**Thomas Connor**:Writing - review & editing.**Jie Gao**:Investigation.**Yujun Wang**:Writing - review & editing.**Yichao Zeng**:Writing - review & editing.**Jindong Zhang**:Conceptualization, Writing - review & editing.**Jinyan Huang**:Resources.**Bochuan Zheng**:Methodology, Software, Formal analysis.**Shiqiang Zhou**:Resources.

## Declaration of competing interest

Authors have no conflict of interest to declare.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2020.108414.

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