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Digital Image Processing and Sequential Convolution Neural Network for an Identification of Elephant

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Abstract

As we know, digital image processing and Deep Neural networks are used to identify people, birds, and Species. DNN has a technique known as Convolution Neural Network CNN, which is used to recognize and classify particular features from images and is also used for analyzing the visual image. The mathematical function denoted by "convolution" is a linear operation in which two functions are multiplied to produce a third function. This third function in the form of matrices is used to extract features from the image. In the CNN model activation function is an important parameter. It is used to learn any kind of continuous and complex relationship between variables of the network. For a binary classification CNN model, sigmoid and softmax are used and for multi-class classification, softmax is used. In our work, our objective is to identify a particular elephant from the dataset of three thousand elephants. We have grouped this dataset under eleven groups. All groups are labeled as a numeric value. The result of the identified elephant is in the form of numeric value. In our work, we have used the CNN sequential model of DNN. The elephant dataset is collected from TamorePingla, it is an elephant captivity in the Surguja district of Chhattisgarh state, India. We have used four layers of the CNN sequential model. Total parameters of this model are trained for two by two kernels and for ten-twenty and three hundred epochs. We have used Rectified Linear Activation Function (ReLU). With this model, it is easy to train and can achieve better performance.

KEYWORD: Artificial Intelligence, Convolution Neural Network, Image Processing, Elephant.

1. INTRODUCTION

We trained a machine learning model using convolution neural networks with the CNN architecture and 3,000,00 images to automatically classify elephants from our camera images obtained from TamorPingla, Surguja District, Chhattisgarh, India. We tested our model on an independent subset of images not seen during training from the Tamorpingla, Surguja District, Chhattisgarh, India, and on an out-of-sample (or "out-of-distribution" in the machine learning literature) dataset of ungulate images from Achanakmar Elephant Rescue center Chhattisgarh, India. We also tested the ability of our model to distinguish empty elephant images from those with elephants, containing a faunal community that was novel to the model.The trained model classified approximately 2,000 images per minute on a laptop computer with 16 gigabytes of RAM. The trained model achieved 98% accuracy in identifying elephants in Chhattisgarh, India, and the highest accuracy of such a model to date. Out-of-sample

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validation from Achanakmar, Chhattisgarh, India achieved 82% accuracy and was correctly identified. We provide a CNN in Python (Deep Learning for Elephant Image Classification) that allows the users to (a) use the trained model presented here and (b) train their own model using classified images of elephants from their studies. The use of machine learning to rapidly and accurately classify elephant images can facilitate non-invasive sampling designs in ecological studies by reducing the burden of manually analyzing images. Our CNN makes these methods accessible to ecologists.

Elephant image classifications are increasingly used to identify elephants in large geographical areas with minimal human involvement and less elephant conflict with Humans (O'Connell et al., 2011). A common limitation is these methods lead to a large elephant image which must be first classified in order to be used in ecological studies (Niedballa et al., 2016; Swanson et al., 2015). The burden of manually viewing and classifying elephant images often constrains studies by reducing the sampling intensity for elephant identification for reduced elephant-human conflict. (e.g., number of more or more elephant images) Limiting the geographical extent and duration of studies. Recently, deep learning has emerged as a potential solution for automatically classifying elephant images. (Chen et al., 2014; Gomez Villa et al., 2017; Norouzzadeh et al., 2018; Swinnen et al., 2014; Yu et al., 2013). We sought to develop a deep learning approach that can be applied across study sites and provide software that ecologists can use for the identification of elephants in their own camera images. Using over three million identified images of an elephant from camera images from two locations across Chhattisgarh, India; we trained and tested a deep learning model that automatically classify elephants. We provide a CNN (Deep Learning for Elephant Image Classification [DLEIC]) that allows researchers to classify elephant images from Chhattisgarh, India or train their own deep learning models to classify elephant images.

2. MATERIALS AND METHODS

We have used camera trapped images as our data set. Methods used in our work is discussed in our work.

2.1. Camera Trap Images

Elephant in our camera images from two locations across the Chhattisgarh, India. (TamorPingla, Surguja District, Chhattisgarh, India) and one location from (Achanakmar, Chhattsgarh, India) were elephant identified manually by researchers (see Appendix SI for a description of each field location). Elephant images were either classified by a single elephant expert or evaluated independently by two researchers; any conflicts were decided by a third observer (Appendix SI). If any part of an animal (e.g., leg or ear) was identified as being present in an elephant images, this was included as an elephant images. If an elephant image did not contain any elephants, it was classified as empty. The elephant images from TamorPingla, Surguja District, Chhattisgarh, India, were not used for training, but were used as an out-of-sample dataset for validation. This resulted in a total of 3,000,000 classified

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elephant images that included 11 elephant (see Table1) across the study locations. We present these elephant images and their classifications for our model development as the Chhattisgarh, India, and Elephant Images (CIEI) dataset. To increase processing speed, elephant images were resized to 256 × 256 pixels following the methods and using the Python script of (Bakhtawer et al., 2022). To have a more robust model, we randomly applied different label-preserving transformations (Cropping, Horizontal flipping, and brightness and contrast modifications), called data augmentation (Krizhevsky et al., 2012). We randomly selected 90% of the classified elephant images for train the model and 10% of the elephant images to test it. However, we wanted to evaluate the our model's performance for each elephant present at each study, so we used conditional sampling in which we altered training testing allocation for the rare situations (four total instances) where there were few classified elephant images of a site. Specifically, with 1-11 classified elephant images for a site (two instances), we used all of these elephant images for testing and none for training (the model was training using only images of these elephant from other sites); for site-elephant pairs with 10-30 images (two instances), 50% were used for training and testing; and for > 30 images per site for each elephant, 90% were allocated to training and 10% to testing (Appendices S3 – S7 Show the number of training and test elephant images for each site). This resulted in 3,839,739 elephant images used to train the model and 356,982 elephant images used for testing.

2.2. Deep Learning Process

As deep learning methods are new to many ecologists, we provide a brief introduction in a supplement (Appendix S2). Following (Bakhtawer et al., 2022), we trained a deep convolution neural network (Binary classification CNN model) architecture (He Zhang et al., 2016) using the sigmoid and softmax are used and for multi-class classification, softmax is used (Advanced Research Computing Center, 2012).

Table 1. Model performance for each elephant or group

Elephant Names	Number of Training Images	Number of Testing Images	Recall	Top 5 Recall	Precision	False-Positive Rate	False-Negative Rate
Duryodhan Male Elephant	8.886	997	0.98	1.00	0.98	0.02	0.02
Ganga Female Elephant	7,252	829	0.91	0.96	0.93	0.07	0.09
Lali Female Elephant	9,125	943	0.89	0.99	0.03	0.07	0.09
Pershuram Male	6,299	759	0.90	1.00	0.90	0.10	0.10

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Elephant							
Raju Male Elephant	7,091	810	0.79	0.96	0.88	0.12	0.21
Sivilbahadur Male Elephant	10,749	1019	0.95	0.94	0.96	0.04	0.05
Sonu Male Elephant	8,629	902	0.91	0.91	0.99	0.06	0.09
Tirathram Male Elephant	9,925	1001	0.79	0.98	0.88	0.02	0.03
Yoglaxmi Female Elephant	8021	965	0.89	0.95	0.93	0.07	0.11
Sawan Male Elephant	10,564	850	0.77	0.99	1.00	0.06	0.11
Total	83,705	9,075					

We used the ReLU activation function, 55 epochs, a back propagation algorithm, (Bengio, &Courville, 2016), and the learning rate (η) and weight decay varied by epoch number as described in Appendix S8. In Appendix S2, we describe the calculation of metrics including accuracy, recall, precision, and false-positive and false-negative error rates. Briefly, recall, and precision is measures of the model's performance at correctly identifying each elephant. We fit the generalized additive model's performance at correctly identifying each elephant. We fit generalized additive models (GAMs) to the relationship between recall and the algorithm (base 10) of the number of elephant images used to train the model; see Appendix S9 for a description of the model. We also calculated the recall and rates of error specific to each of the eleven datasets from which elephant images were acquired.

2.3.Model Validation

To evaluate how our model would perform for a completely new study site in Chhattisgarh, India, we used a dataset of 5,900 classified elephant images (Duryodhan Male elephant, Ganga Female Elephant, Lali Female Elephant, Parshuram Male Elephant, Raju Male Elephant, Sivilbahadur Male Elephant, Sonu Male Elephant, Tirathram Male Elephant, Yoglaxmi Female Elephant, Sawan Male Elephant) from TamorPingla, Surguja District, and Achanakmar Chhattisgarh, India, by running the trained model on these elephant images. We also evaluated the ability of the model to operate on elephant images with a completely different position in elephant images (from Chhattisgarh, India) to determine the model's ability to correctly classify elephant images as having an elephant or being empty when encountering a new elephant that it has not been trained to recognize. This was done using 3.2 lakh classified elephant images from the TamorPingla, Surguja District, and Achanakmar, Chhattisgarh, India, dataset (Swanson et al., 2015).

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3. RESULTS

Our model performed well, achieving 97.6% accuracy in identifying the correct elephant with the top guess. The top-5 accuracy was > 99.9%. Figure I provide examples of elephant image classification by the model. The model confidence in the correct answer varied, but was mostly > 95%; see Figure 2 for confidence for each elephant image for eleven example elephants.

(a) Correct Classification by model (b) Incorrect Classification by model

Model Guess	Confidence (%)	Model Guess	Confidence (%)
All Single Elephant	98.14	Multiple Elephant and Mans	49.11

Answer from human classification
Duryodhan

Answer from human classification
Yoglaxmi, Sawan, Parshuram

FIGURE 1 Example of elephant images that could be difficult to classify. The model correctly identifies an elephant (a) by seeing only its hindquarters and tail (right side of the elephant image). The model incorrectly classifies another elephant (b), as only an ear is visible in the elephant image; note that the model has relatively low confidence in the top guess for this elephant image. Nevertheless, the elephant is within the top-5 guesses for this elephant image, so while it is incorrect, it counts towards the top-5 recall for the elephant.

We present a confusion matrix comparing the classification by the model with those from manual classification. Supporting a similar finding for camera trap images (Norouzzadeh et al., 2018), and a general trend in deep learning (Goodfellow et al., 2016), elephants and groups that had more elephant images available for training were classified more accurately (Figure 2, Table 1). GAMs relating the

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number of training elephant images with recall predicted 95% recall could be achieved. When represent the confidence assigned by all of the top-5 guesses by the model for each of these eleven example elephants when it was present in an elephant image. The dashed line represents 95% confidence; the majority of model-assigned confidences were greater than this value

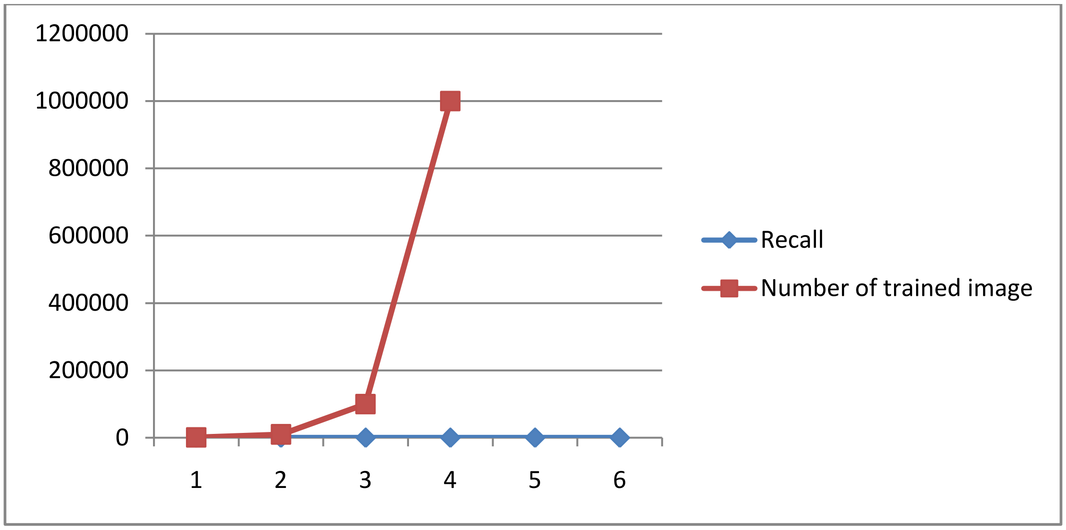

FIGURE 2. Model recall (the ability of the model to recognize an elephant) increased with the size of the training dataset for that elephant. The point represents each elephant or group of elephants or group of elephants. The line represents the result of generalized models relating the two variables.

Approximately 54,000 training elephant images were available for an elephant group. However, for several elephant groups, 95% recall was achieved with fewer than 50,000 elephant images (Figure 3). We found there was not a large effect of daytime versus night-time on accuracy in the model as daytime accuracy was 98.2% and night-time accuracy was 96.6%. The top-5 accuracies for both times of day were ≥ 99.9%. When we subsided the testing dataset by study site, we found that site-specific accuracies ranged from 90% to 99%. When we conducted out-of-sample validation by using our model to evaluate elephant images of ungulates from Chhattisgarh, India, we achieved an overall accuracy of 81.8% with a top-5 accuracy of 90.9%. When we tested the ability of our model to accurately predict the presence or absence of an elephant in the elephant images using the Chhattisgarh, India, Dataset, we found that 85.1% were classified correctly as empty while 94.3% of elephant images containing an elephant were classified as containing an elephant. Out trained model was capable of classifying approximately 2,000 elephant images per minute on a Macintosh laptop with 16 gigabytes of RAM.

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4. DISCUSSION

To our knowledge, our model achieved the highest accuracy (97.6%) to date in using deep learning to classify wildlife in our camera images (a recent paper achieved 95% accuracy; Norouzzadeh et al., 2018). This model performed almost as well during the night as during the day (accuracy = 97% and 98%, respectively). We provide this model as a Python (DLEIC), which is especially useful for researchers studying the elephant and groups available in this package (Table 1) in Chhattisgarh, India, as it performed well (82% accuracy) in classifying ungulates in an out-of-sample test of elephant images from Chhattisgarh, India. The model can also be valuable for researchers studying another elephant by removing elephant images without any animal from the dataset before beginning manual classification. We achieved high accuracy in separating empty elephant images from those containing elephants in a dataset from Chhattisgarh, India. This CNN can also be a valuable tool for any researchers that have classified elephant images, as they can use the CNN to train their own model that can then classify any subsequent elephant images collected. The ability to rapidly identify millions of elephant images from our camera images can fundamentally change the way ecologists design and implement wildlife studies. The burden of classifying elephant images has led ecologists to limit the duration and size of elephant image studies (Kelly et al., 2008; Scott et al., 2018). By removing this burden our camera images can be applied in more studies including monitoring invasive or sensitive elephant images, long-term ecological research, and small-scale occupancy studies.

CRediT authorship Contribution statement

Bakhtawer Shameem: Conceptualization Methodology, Software, Validation, Investigation, Writing-original draft, Visualization, Validation.

BhavnaNarain: Conceptualization, Formal analysis, Supervision, Writing-review & editing.

Declaration of Computing Interest

The author declare that they have no known competing financial interests or personal relationship that could have appeared to influence the work reported in this paper.

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