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Review Article

ANIMAL DETECTION USING DEEP LEARNING ALGORITHM

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ABSTRACT

Checking of wild animal in their common environment is crucial. This proposed work develops an algorithm to detect the animals in wild life. Since there are many different animals manually identifying them can be a difficult task. This algorithm classifies animals based on their images so we can monitor them more efficiently. Animal detection and classification can help to prevent animal-vehicle accidents, trace animals and prevent theft. This can be achieved by applying effective deep learning algorithms.

Keywords: Animal Detection and Classification, Deep Learning Algorithms.

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INTRODUCTION

Machine learning is a subsystem of artificial intelligence that makes systems involuntarily learn and progress from experience without being programmed. Machine learning focuses on the growth of computer programs that can access data and utilize it to learn for themselves. The learning process starts with interpretation or data, like examples, previous model, or suggestions, in order to take improved decisions in the future. The principal aim is to permit the computers train themselves without human intrusion or assistance and corrects its mistakes themselves through this learning.

Deep neural networks are the collection of algorithms that have placed new records in precision for several vital problems; Convolutional neural network (CNN) is a type of deep neural networks, most generally applied for investigating visual images. Compared to other image classification algorithms, CNNs employ fairly modest preprocessing. This liberty from past knowledge and human intervention in feature design is a key benefit of Convolutional neural network (CNN). They have several applications in the field of image and video recognition, recommendation systems, image classification and medical image processing.

Examining wild animals in their natural environment is an essential task in ecosystem. Due to the enormous growth in human inhabitants and the increase in hunt of economic development makes excessive exploitation of natural resources, fast, innovative and significant changes in the Earth's ecosystems.

An expanding region of the land surface has been changed by human activity, modifying natural life populace, habitat and behavior. More fatally, many wild animals on the Earth have disappeared, and many species are locomoted into new places where they can disturb all natural and human resources.

LITERATURE SURVEY

The purpose of animal detection systems is to prevent the accidents due to animal-vehicle collisions. This results to death, injury and also property damage for humans.

The present state of art for animal detection is discussed in this paper. Interestingly, many image processing algorithms were proposed for animal detection using different techniques.

A. Animal Detection Using Template Matching Algorithm

In this paper, reviews on different object detection algorithms were proposed. Considering efficiency, proposed system has low false positive rate and false negative rate.

Template Matching

Template matching is a method for identifying small parts of an image which should match the template image. Normalized cross correlation is introduced to perform template matching. In signal processing, cross-correlation is a measure of similarities between two waveforms as a component of time-slack applied to one of the waveforms.

That too Called the sliding point product or/and sliding inner-product. Most commonly, template matching is used for searching a long-duration signal for an identified feature. For applications involving image processing techniques to find the brightness of an image, the template can differ due to lighting and exposure surroundings, so the images can first be normalized. This is usually done at each step by subtracting the mean and separating by the standard deviation. In this paper we have discussed the feature based template matching technique using NCC.

B. Identifying, Counting, and Describing Wild Animals in Camera-Trap Images with Deep Learning

In this research, the location and activities of animals in the wild is known prior using deep learning. This paper examines the ability to involuntarily and accurately gather camera trap image data, also a motion sensor is also present for collecting the movements of wildlife. Although, extracting data from these images remains a costly, sustained, physical task. It's noticeable that such information can be automatically extracted by using deep learning.

A Deep convolutional neural network is trained to recognize, count, and illustrate the behaviors of 48 breed from 3.2-million image Snapshot Serengeti dataset. The network can automatically recognize animals with 93.8% of accuracy. More significantly, if the system classifies only self-confident images, it automates animal identification

to 99.3% of data. But still the performance remains likewise 96.6% accurate, saving more than 8.4 years of human labeling effort (over 17,000 hours) on this 3.2-million-imagedataset. This effectiveness highlights the significance of using deep neural networks to automate the extraction of data from camera trap images. The results of this study emphasize that this technology can enable inexpensive, significant, and real-time collections in the natural habitats of large numbers of animals.

BLOCK DIAGRAM

A. Convolutional Neural Network

A convolutional neural network (CNN) is a subset of artificial neural networks which uses perceptron, a machine learning algorithm for supervised learning to analyze large amount of data. CNNs can be used for image processing and natural language processing (NLP) applications and any kind of cognitive tasks. A convolutional neural network (CNN) has an input layer, an output layer and many numbers of hidden layers. Few of these layers are convolved, using mathematical models to carry on results to succeeding layers.

- Input image will have the raw pixel values of color channels Red(R), Green (G), Blue (B).
- The next layer is called, CONV layer. This layer will calculate the output of neurons that are connected to local regions to the input layer. Each calculates a point product between their weights and a small area connected to the input layer.
- Third layer is called RELU layer, which will apply a unit wise activation function. This makes the size of the volume unaffected.
- The next layer is called the POOL layer, which performs down sampling operation along the spatial dimensions (width and height) resulting in size such as [16x16x12].
- Last layer is FC (i.e. fully-connected) layer; this layer will calculate the class scores, resulting in volume of size. Like traditional Neural Networks, each neuron in this layer is connected to all the weights in the previous set.

B. Convolutional Layer

Fig. 1 shows the concept of convolutional layer; this layer extracts features from an input image. Convolution conserves the association between pixels by learning image features by means of small squares of input image data. In this mathematical operation, two inputs such as image matrix and a filter is used. Convolution of an image data with various filters can do operations like edge detection, blur and sharpening of images.

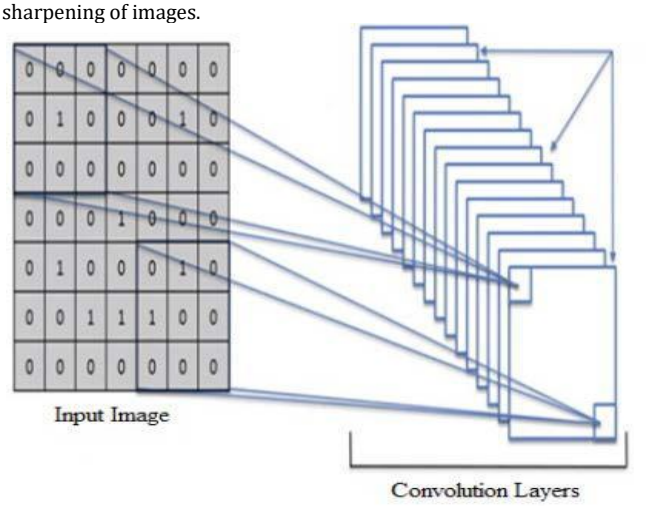

Fig. 1: Convolutional Layer

C. Pooling

Pooling layer would lessen the number of parameters when a large image is given as input. Max pooling is done by taking the largest element from the revised feature map. The objective of max pooling is to down sample an input image, reducing its dimensions etc. This is shown in Fig. 2.

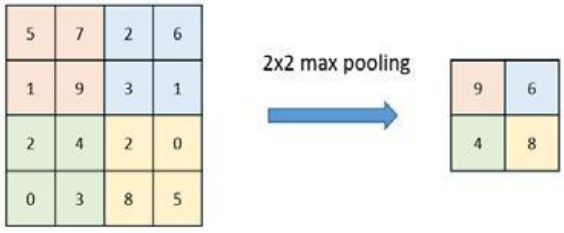

Fig. 2: Pooling Layer

D. Flattening

Flattening is the procedure for converting the two dimensional array set into a single, long continuous linear vector. It receives the output from the convolutional layers, flattens its structure to create a single, long feature vector to be use the next layer for the final classification. This is shown in Fig. 3

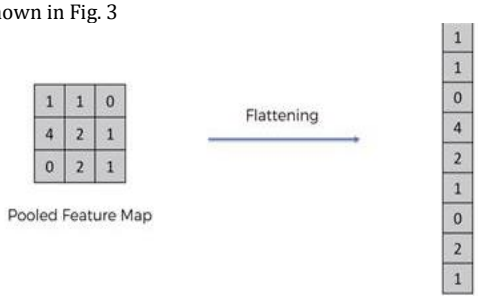

Fig. 3: Flattening Layer

E. Fully connected

Fig.4 shows the hidden layers inside a Convolutional Neural Network that are called as Fully Connected Layers. These are a specific type of hidden layer which must be used within the CNN. This is used to combine the features into more attributes that predict the outputs more accurately

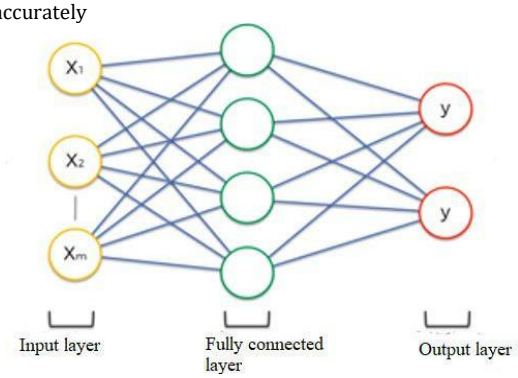

Fig. 4: Fully Connected Layer

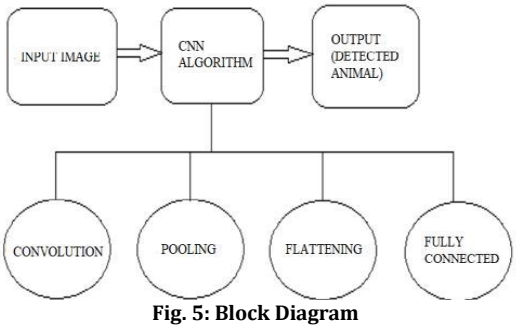

Fig. 5: Block Diagram

Fig.5 shows the block diagram of the animal detection using deep learning algorithm

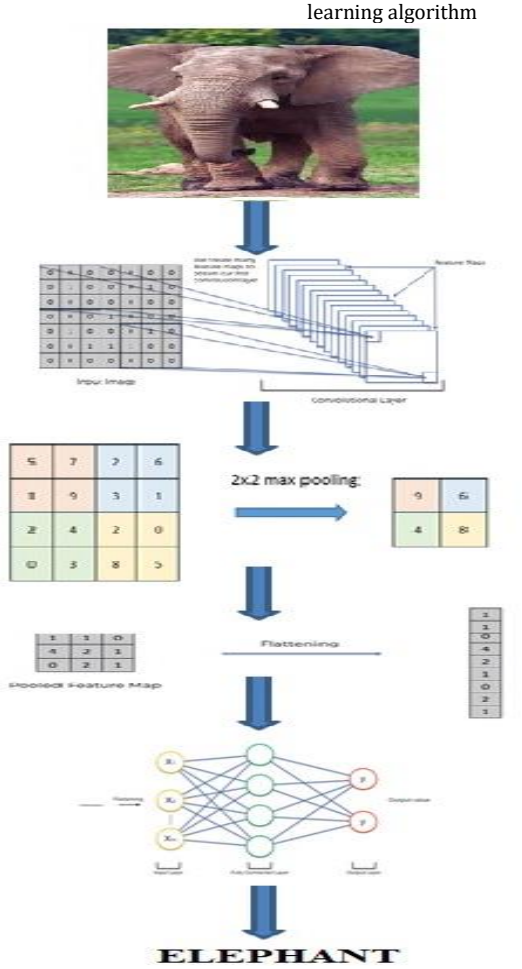

Fig. 6: Flow Diagram

Fig. 6 shows the flow diagram of animal detection.

DATASET

The dataset used here is a collection of image data that contains various images of animals. The Dataset is splitted into train and test in the ratio of 75:25 respectively.

A. Train Dataset Elephant Train Dataset

Cheetah Train Dataset

Fig. 7: Cheetah Train Dataset

B. Test dataset Elephant Test Dataset

Fig. 8: Elephant Test Dataset

Cheetah Test Dataset

Fig. 9: Cheetah Test Dataset

RESULT

A. Detection of Elephant

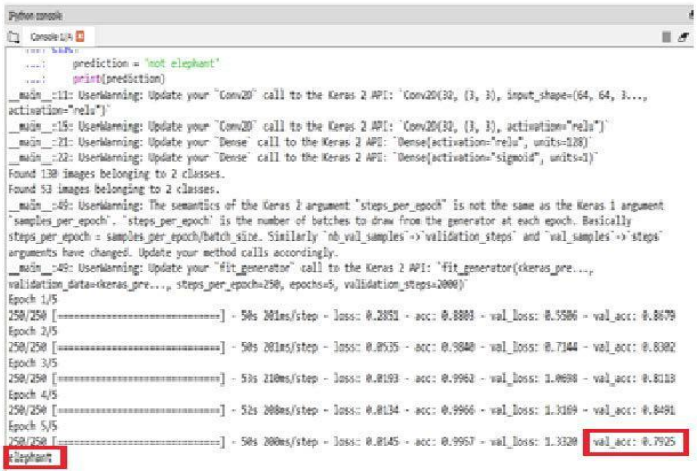

Fig. 10: Accuracy of Detected Elephant

Fig. 11: Detected Elephant

B. Detection of Cheetah

```
Console 1/A
  classifier.add(Dense(output_dim = 1, activation = 'sigmoid'))
Found 130 images belonging to 2 classes.
Found 53 images belonging to 2 classes.
F:/input images.csv/graph.py:57: UserWarning: The semantics of the Keras 2 argument `steps_per_epoch` is not the same
the Keras 1 argument `samples_per_epoch`. `steps_per_epoch` is the number of batches to draw from the generator at ea
epoch. Basically steps_per_epoch = samples_per_epoch/batch_size. Similarly `nb_val_samples`->`validation_steps` and
`val_samples`->`steps` arguments have changed. Update your method calls accordingly.
  nb_val_samples = 2000)
F:/input images.csv/graph.py:57: UserWarning: Update your `fit_generator` call to the Keras 2 API:
`fit_generator(<keras_pre..., validation_data=<keras_pre..., steps_per_epoch=250, epochs=5, validation_steps=2000)`
  nb_val_samples = 2000)
Epoch 1/5
250/250 [==============================] - 58s 233ms/step - loss: 0.2462 - acc: 0.8980 - val_loss: 0.6937 - val_acc:
0.8679
Epoch 2/5
250/250 [==============================] - 53s 212ms/step - loss: 0.0514 - acc: 0.9837 - val_loss: 0.7702 - val_acc:
0.8679
Epoch 3/5
250/250 [==============================] - 52s 209ms/step - loss: 0.0154 - acc: 0.9960 - val_loss: 1.1240 - val_acc:
0.8491
Epoch 4/5
250/250 [==============================] - 52s 207ms/step - loss: 0.0083 - acc: 0.9984 - val_loss: 1.1751 - val_acc:
0.8679
Epoch 5/5
250/250 [==============================] - 52s 208ms/step - loss: 0.0232 - acc: 0.9910 - val_loss: 0.5180 - val_acc:
0.8679
cheetah
```

Fig. 12: Accuracy of Detected Cheetah

Fig. 13: Detected Cheetah

CONCLUSION

Thus this project uses Convolutional Neural Network (CNN) algorithm to detect wild animals. The algorithm classifies animals efficiently with a good number of accuracy and also the image of the detected animal is displayed for a better result so that it can be used for other purposes such as detecting wild animals entering into human habitat and to prevent wildlife poaching and even human animal conflict.

FUTURE SCOPE

This work can be further extended by sending an alert in the form of a message when the animal is detected to the nearby forest office. Furthermore it can be used to reduce human wildlife conflict and also animal accidents.

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