A REVIEW ON WILD ANIMAL DETECTION AND CLASSIFICATION

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ABSTRACT

As humans are encroaching the forest land at a higher pace to satisfy their own greeds and needs, wild species are continually losing their natural habitat. This has in turn led to these wild animals moving out of forests and further into the human habitat. Hence there is a need to detect an animal and classify it so as to measure the degree of harm it can cause to human beings. In this paper we are going to discuss some of the possible technical solutions to detect and classify wild animals as proposed by researchers.

Keywords: Wild Animals

I. INTRODUCTION

Wild Animals have always been a source of interest to researchers due to their peculiar behaviour and the extreme environments in which they survive. However there has been a threat to their home by humans which is in turn creating devastated impact on humans. Animals have started to move out of forests in search of shelter and food thereby putting human lives at risk. It is also important to note that the live of animals is also at risk as humans may harm them in the act of saving themselves.

All these problems have led to the need for a system that detects and classifies the wild animals that helps in preventing the threat caused by humans to animals and vice-versa.

The primary objective of the study is to evaluate the effectiveness of various algorithms or models used to detect and classify the wild animals. Animals were detected using Convolution Neural Networks and classified using various algorithms such as Support Vector Machine(SVM), k-Nearest Neighbor(kNN), etc.

II. RELATED WORK

Nidhal K. El Abbadi et al., (2020) [1] put forward a Deep Convolution Neural Network (DCNN) to basically detect and classify vertebrate classes namely mammals, amphibians, reptiles, birds and fishes from digital images.The required dataset consisiting of 12000 images was obtained from CalTech Vision Lab out of which 9600 were used for training and rest for testing. The proposed architecture made use of 3 convolution layers each followed by a Maxpooling layer and Softmax layer was used as a final one to classify the images. The various layers used were Convolution, ReLu and Pool. The model was trained with images of different sizes such as 20*20, 40*40, 50*50 and so on and also with different epochs such as 10, 20, 50, and so on. The best result was obtained when the image size was 50*50 and the epoch was 100. Even though various activation functions and optimizers were used, the combination of ReLu and Adam outperformed others. After performing multiple tests, the accuracy reached 97.5% which was the best.

Brian H Curtin et al., (2020) [2] used a Raspberry-Pi based camera system associated with deep learning model for detecting wildlife. TensorFlow and Keras were used to build a CNN which consisted of 2 Convolution layers both of which were followed by Maxpooling layer. The CNN runs on Raspberry Pi 3B+. The required databases were obtained from ImageNet and VIPeR wherein out of 3600 images, 1568 images were of Snow Leopard's, 1262 images of Human and rest of natural background environment. A total of 128 units, ReLu activation function and ADADELTA were used. The acquired images were split for training, testing and validating int the ratio of 80:10:10 respectively. 10 epochs, 250 steps and 150 validation steps were performed. Quality of results were measured using accuracy, precision and recall. The accuracy ranged between 74% to 97% where the accuracy for pre-downloaded images was more than that of live images.

Sonail Jamil et al., (2020) [3] made use of Deep Convolution Neural Network(DCNN) supplemented by k-Nearest Neighbor(kNN) to detect animals. The dataset of animals was primarily divided into 4 classes – Snow Leopard, Marco Polo Sheep, Himalayan Bear and other animals. In order to extract features several DCNNs such as AlexNet, ResNet, VGG-K, Inception v3 were used. And Support Vector Machine(SVM) and kNN were used as classifiers. A training dataset of 280 images was used to build the model. The model was split into 2 parts namely Feature Extraction and Classification.The model which uses Inception v3 as a DCNN extracts features using convolution layers and then classifies it using fully connected and softmax layers. The accuracy was measured using Confusion Matrix consisiting of several parameters. It can be noted that Inception v3 with kNN classifier outperformed other combinations with an accuracy of 98.3% and a minimal error of 2%.

G Supriya et al., (2019) [4] proposed a Deep Convolution Neural Network (DCNN) to classify the input animal images obtained from camera trap networks for wildlife monitoring and analysis. The number and size of blobs in the footprint of an animal was used to recognize it and further predict it's age. Trainable fully convolutional layers were used for feature extraction and fully connected layers for classification. Various state-of-art machine learning algorithms such as SVM, kNN and ensemble tree were used for classification. DCNN was trained using both balanced and unbalanced datasets. For unbalanced datasets, FMeasure was used along with accuracy to measure the performance. An accuracy of 96%-97% was reported with a perfect 100% during initial training.

Xuefeng Liu et al., (2019) [5] suggested real-time classification of marine animals by combining an embedded system along with MobileNetV2, based on CNN and transfer learning. The experiment used some of the data from underwater cameras and others were obtained from Internet(ImageNet database). The model is trained using small-scale datasets. Since dataset was small in scale, data enhancement was used to improve overall performance of training network. Transfer learning was introduced to solve the problem of insufficient datasets. The whole dataset was divided into 7 categories – fish, shrimp, scallop, crab, lobster, abalone and sea cucumber. There were totally 8455 sheets with each category consisting of 1000-1400 sheets. The dataset was divided in the ratio of 80:20 for training and validation respectively. The proposed model was compared alongside Inception v3 and MobileNetV1. MobileNetV2 model trained by transfer learning gave the best validation set accuracy of 92.89%.

Durmus Ozdemir et al., (2022) [6] came forward with a decision support software based on mobile, integrated with a deep learning model to classify and detect insects at the order level. The required data was collected from Kaggle with 25820 data used for training and 1500 data used for testing. A comparitive study was carried out using SSD MobileNET, YoloV4 and InceptionV3 deep learning method, using Faster RCNN. The collected images were subjected to pre-processing and each method was run through different number of epochs. It was clearly concluded that the Faster RCNN model came out to be the most successful one amongst others.

L. G. C. Vithakshana et al., (2021) [7] proposed a Convolution Neural Network(CNN) based on IoT to monitor the ecosystem and classify the animals. The data(audio clips) was collected from the place where the hardware(devices in IoT) was deployed. Mel-frequency cepstral coefficients was used to pre-process the collected data. A CNN architecture based on TensorFlow was used for the training the model. Different optimizers such as AdaDelta, Gradient Descent, RMSProp, AdaGrad, Adam and Momentum were used to train the network and the confusion matrix was recorded for each. It was crystal clear that AdaDelta, Gradient Descent, RMSProp equally outperformed others with an accuracy of 91.3%.

Tibor TRNOVSZKY et al., (2017) [8] used a Convolution Neural Network(CNN) to classify the input animal images. The dataset consisted of 5 classes(fox, wolf, bear, hog and deer) with 100 images in each class. The proposed method was compared with the image recognition methods such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Local Binary Patterns Histograms (LBPH) and Support Vector Machine (SVM) which are well known. The CNN was divided into 8 blocks consisting of Convolution layer, ReLu and Maxpooling layer. The model was trained with varying ratios of training and testing data i.e., from 40:60 to 90:10. The confusion matrix was constructed for the proposed CNN. The best precision of 98% was achieved by the proposed CNN for the bear class.

III. Comparison Among Models

The comparision of various models proposed by different authors is given by Table 1 depicted below.

Table-1: Comparision Among Models

Title	**Reference**	**Techniques/Technology used**	**Accuracy**
An Automated Vertebrate Animals Classification Using Deep Convolution Neural Networks	Nidhal K. El Abbadi et al., [1] 2020	Deep Convolution Neural Network	97.5%
Deep Learning for Inexpensive Image Classification of Wildlife on the Raspberry Pi	Brian H Curtin et al., [2] 2020	Raspberry-Pi based camera system, Convolution Neural Network, TensorFlow, Keras	74%-97%
Deep Learning and Computer Vision-based a Novel Framework for Himalayan Bear,	Sonail Jamil et al., [3] 2020	Deep Convolution Neural Network such as AlexNet, ResNet, VGG-K, Inception v3,	98.3%

Marco Polo Sheep and Snow Leopard Detection		k-Nearest Neighbor, Support Vector Machine	
Integrated Animal Recognition and Detection Using Deep Convolutional Neural Network	G Supriya et al., [4] 2019	Deep Convolution Neural Network, k-Nearest Neighbor, Support Vector Machine, Ensemble tree	96%-97%
Real-time Marine Animal Images Classification by Embedded System Based on Mobilenet and Transfer Learning	Xuefeng Liu et al., [5] 2019	MobileNetV2, CNN, Transfer Learning	92.89%
Comparison of Deep Learning Techniques for Classification of the Insects in Order Level With Mobile Software Application	Durmus Ozdemir et al., [6] 2022	Deep Learning	-
IoT based animal classification system using convolutional neural network	L. G. C. Vithakshana et al., [7] 2021	Convolution Neural Network, Internet of Things(IoT)	91.3%
Animal Recognition System Based on Convolutional Neural Network	Tibor TRNOVSZKY et al., [8] 2017	Convolution Neural Network	98%

IV. CONCLUSION

The interdependence of humans and animals continue to live till the day the earth exists. The harm caused by one to another has been an issue of concern past several centuries. As animals are less intelligent than humans and as humans have equipped themselves with latest technology, several steps can be taken by them to protect themselves from animals. Any of the above proposed methods can be used for advantage depending on the application.

V. REFERENCES

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