Proceedings of the Third International Conference on Artificial Intelligence and Smart Energy (ICAIS 2023)
IEEE Xplore Part Number: CFP23OAB-ART; ISBN: 978-1-6654-6216-7

A Comparison of Different Learning Algorithms for Wildlife Detection and Classification in Animal Conservation Applications

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2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS) | 978-1-6654-6216-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICAIS56108.2023.10073833

Abstract:

In order to track animal movement patterns, habitat use, population demographics, human-wildlife conflict, vehicle-animal collisions, snare and poaching occurrences, and epidemics, it is essential to monitor wildlife. Over time, accidents between wildlife and vehicles have increased in frequency on both rural and hilly roads and highways. Road deaths are sometimes caused by wildlife crossing the road at inopportune moments. The identification and categorization of animals from picture and video sequences is a popular area of study. Current methods for wildlife monitoring depend on image processing. This study provides a reliable method for detecting wildlife and divides it into two categories: animal-human conflict and animal-vehicle collision. Different learning approaches are employed to classify the animals with the use of datasets and a live motion sensor. Applications for wildlife have employed machine learning and deep learning extensively. This article discusses a variety of learning techniques and offers the authors' answers. There may be a chance to identify and categories wildlife when it enters a living area, an agricultural region, or a roadway. Various authors provide various classification and identification strategies based on Camera trap and Dataset.

Keywords: Deep Learning, Animal Detection, Convolutional Neural Network, Thermal Images, Classification.

I. INTRODUCTION

Wildlife monitoring is a crucial and developing field due to the numerous real-world applications. When animals roam the roadside and in residential areas, signal indication warns people. Various techniques are used to categorise and identify animal activity. [1]. Applications are crucial in preventing human-wildlife conflict, wildlife-vehicle collisions, etc. in the real world. Animal classification, detection, and identification can be applied to all of these applications.

Learning representation is a key machine learning method used in artificial neural networks. Deep learning is a component of machine learning. Three categories of learning exist: supervised, semi-supervised, and unsupervised. [1] It is crucial to check on the biodiversity of the animals. The system's objective is to create an algorithm for spotting animals in the wild. Since there are so many different kinds of animals, it might be challenging to distinguish between them all. With the help of this programme, species can be classified based on visual information and keep a closer eye on them. The methods used in creature categorization and detection are based on protecting wildlife and minimising collisions between animals and moving vehicles. The adoption of efficient deep learning algorithms makes this feasible. A particular learning algorithm called ConvNet is also referred to as a feedforward neural network. Due to its extreme accuracy, Convolutional Neural Network [2] will be used for image classification and recognition.

II. LITERATURE SURVEY

This paper [4] focuses on machine learning techniques for wildlife image-based detection, specifically using Random Forest, Decision Tree, and Support Vector Machine implementations for thermal images using HOG and CNN. The techniques described in this study use thermal camera datasets to show images of wild deer moving through San Antonio, Texas. By reducing the dataset size or employing high filtration, the detection accuracy will be enhanced even more in the future. Currently, [5] all deal with the issue of vehicle-animal accidents on the side of the road. In order to address this issue, this paper introduces computer vision and machine learning algorithms for detecting animals on highways. Donkeys and capybaras were utilised to train the models. Two Yolov4 (You only look once) convolutional neural network variants were used: Yolov4 and Yolov4-tiny. The training involved using previously trained models. Tests for detection were performed on 147 images. The accuracy rates for Yolov4 and Yolov4-tiny were 84.87% and 79.87%, respectively. This system decreases animal fatalities while enhancing traffic safety.

Based on classification and detection, this researcher's contribution to preventing wildlife poaching, culling, and on-road accidents. Camera trap networks are essential for taking pictures of moving objects and capturing quick videos of animals. This paper[3] uses deep learning techniques like Region-based Convolutional Neural Networks, Fast-RCNN, and Faster-RCNN. As a result, researchers used the IEGC method to detect an animal using DCNN on a set of images obtained from a camera trap. The author wants to protect agriculture and human lives from animal predation. Using a modern strategy, such as machine learning techniques, this problem was resolved. The Raspberry Pi is implemented using CNN and IoT[4]. Using a single shot, detection technology, an object can be found and categorised.

Using the Template Matching algorithm and detection from camera trap images, a convolutional deep neural network automates the process of classifying wildlife. This method makes use of image-based categorization. Researchers are more successful and swifter in tracking the animals [1] to lessen future incidents of animal-vehicle collisions and human-animal conflict on the roadside. This study outlines a method for creating a large number of thermal images that have been labelled and then processed by a colour image object detector. Automatic object identification is its primary objective, and this method is applied to various images with the aid of DCNN. A Pretrained network, various camera images, and 3DLidar are used in the proposed system to detect objects [5].

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The author's intention is to protect humans from animals before suggesting an animal detection system. Features cannot be changed, and fuzzy logic underlies thermal imaging. The proposed system makes use of features like LBP, SMM, and MAM. In order to test the model, 1800 images are used from the thermal dataset, which includes more than 10 different animal images from FLIR. Additionally, this model's accuracy is 97% [6]. Wildlife observation is a crucial task in modern scientific research. The majority of the information on wildlife is gathered in video for research purposes. Convolutional neural networks are a technique for classifying images and videos. With the aid of RNN, CNN models the temporal aspect of the video, and each frame is highlighted separately [7]. A static camera was used for detection and an animal-borne camera was used to classify behaviour in the experimental work, which was set up for seal activity inside salmon nets by the sea.

The authors of this study contend that DCNN is a subset of VCRPCN. Additionally, animal traits that show up in camera-trapped images for automatic classification of wildlife animals. There are 500 images of animals in total. Low-resolution images are often taken at night. The effectiveness of the suggested method is evaluated using cross-validation. This method for object detection uses the same data set and achieves a high accuracy when compared to the current strategies. There has been a 21% improvement in average accuracy [8]. In this study, Vertebrate animals are found in digital photos and identified and classified using a Deep Convolutional Neural Network. Computer vision is one of the most often discussed topics in the field of visual monitoring. Here, a ConvNet architecture was employed to convert pictures from the input volume to the output volume. This design has a number of network layers, including Convolution, ReLU, Pool, and Fully Connected. The 2400 photos are categorised using an image classification system. The output performance of a detecting system is 97.5% when the image size is 50*50[9].

Feature extraction, detection, and classification are essential tasks in a computer vision system. In this research, we offer the Shi-Tomasi corner detector, a detection technique that includes the two characteristics SURF and SIFT. It takes into account the Caltech-101 picture dataset [10] for experimental work. The identification accuracy is increased to 86.4% using an adaptive boosting method with the aid of a Shi-Tomasi, RF Classifier, and its characteristics.

Animal-vehicle crashes and conflicts involving people and other animals regularly result in injuries and, in some instances, fatalities. As a result, reducing the HAC and AVC is the goal of this research. With the use of the Deep Learning Algorithm, object identification is introduced in this study. In this study, we combined the BCMTI dataset with the Snapshot Wisconsin dataset. From the filtered pictures, ConvNet is used to recognise objects [11]. 98% of the time, our system spotted the item.

In order to manage wildlife and preserve biodiversity, it is essential to track and detect animal activities using camera trap photos and recordings [15]. Introduce a new technology for image analysis and recognition along with a machine learning algorithm to create deep learning models, such as the TensorFlow hub-FasterRCNN+InceptionResNet V2 network used to analyse infrared images in both colour and black and white of 10 different wild animals from the European zone [12]. The suggested system has a 94% detection rate, a 71% classification rate for animal names, and a 93% identification rate for specific species.

In this article, a deep convolutional neural network for animal identification was used to locate a big panda [13]. Identification was a major issue with several previous approaches. Using CNN, a subset of deep learning methods for face recognition, we were able to identify specific giant panda individuals. In the dataset, 95% of the pandas were properly recognised by the model. Our system will be used for long-term support (LTS) for monitoring, as well as other datasets for species categorization and detection, in the future.

The Movidius Neural Compute Stick was used by Divya Meena et al [17] for detection and the AdaBoost Classifier for object categorization. The characteristic of the item is extracted using the Multi-Block Local Binary Pattern. The AlexNet dataset includes the trained pictures. The system uses the AoI categorization algorithm to arrive at a result of 96.8%. A novel-based Animal breed categorization problem was put out by Divya Meena et al. [18]. The photos are classified using Fisher Vector Stack Autoencoder and Multi-Part Convolutional Neural Network (MP-CNN). The model has a 99.95% accuracy rate.

The responsibility of monitoring wildlife is crucial nowadays to prevent accidents between animals and vehicles and human-wildlife conflict [14]. The primary emphasis of this work is the automated detection and identification of species and particular surveillance operations using deep learning technology to store the data in the form of video and photos. A deep learning framework is utilised for binary classification and multiclassification in automated image recognition. The accuracy of the two classes is 98.05% and 90.32%, respectively. [15] suggested a technique for detecting animals based on FLIR camera data collected during wildlife monitoring. Animal detection uses elements of the DCNN. The methods for classification include KNN, Decision trees, and SVM. It obtains a 91.4% accuracy on the Camera Trap dataset.

These were the overarching paper concepts that we went through and which would aid in the efficient operation of our system.

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III. RESULTS AND DISCUSSION

A. Methodology

Deep Learning includes convolutional neural networks (CNNs) [21] as a subset. In an artificial neural network, machine learning is included. includes deep learning. The given image is processed by CNN for the purposes of image detection, classification, and processing. There are many hidden layers in the crucial input and output layer. Camera traps are used to capture the input image at either day or night [22]. Convolution, the following layer, uses data from a dataset or a FLIR camera to create the image. Each binary pixel, which can be either 0 or 1, contributes to the creation of an image. That image is capable of being enhanced, blurred, and sharpened for improved clarity. Convolution is followed by a layer called pooling. Depending on the request or instruction of the user, it removes the noisy data from the pixel data. Megapixels require a lot of computation time. To reduce the size by n times is the main objective. Processing time is thus shortened. The machine cannot operate in a 2D array due to pooling. Make a single-dimensional array out of a two-dimensional array. The final product is a long, simple linear with an attractive shape that is then transmitted into a fully connected layer is shown in Figure 1. For a few of the characteristics, this layer is used to accurately forecast the desired output

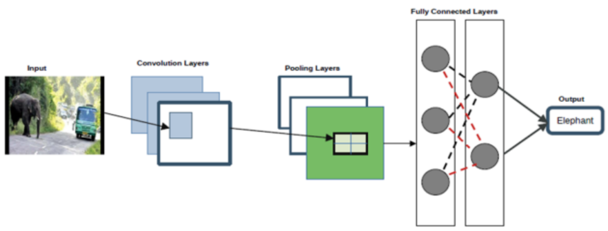

FIGURE 1: Convolutional Neural Networks

B. SURVEY REPORTS

In Tamil Nadu, the study was conducted in districts such as The Nilgiris, Erode, Krishnagiri, and Coimbatore[19] is shown in Figure 2. This district was specifically chosen for research because it had a higher rate of human death due to human-wildlife conflict and Animal Vehicle collisions. Based on reports from the Tamil Nadu Forest Department, this graph depicts human-Elephant conflict[20] and vehicle-animal collisions[21] in the Nilgiris is shown in Figure 3.

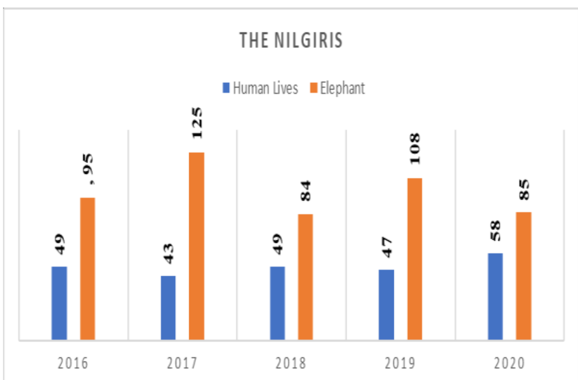

FIGURE 2: Human-Elephant Conflict.

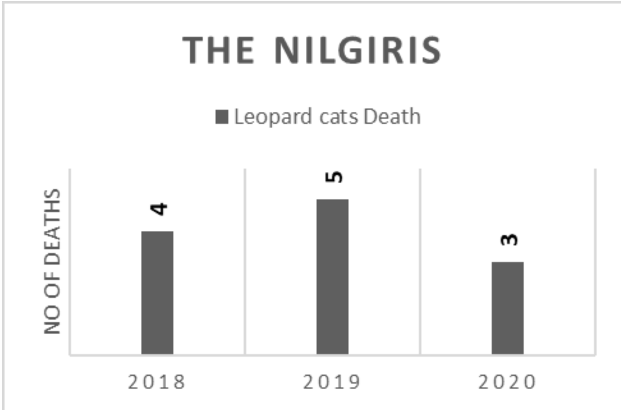

FIGURE 3: Human-Elephant Conflict.

C. SUMMARY OF RELATED WORKS

Ref	Year	Objective	Method	Dataset	Image types	Limitation
[4]	2021	Crop Protection from Animal Intrusion.	RCNN and Single Shot Detection technology, Twilio	Pi Camera	Standard and the NoIR version	APP based model & Mobility
[5]	2021	Object Annotation	DCNN, YOLO	FLIR, BUDIR	RGB and Thermal	There are only a few annotation classes that it supports.
[16]	2021	Animal Detection	Yolov4 & Yolov4 tiny	Google Images	Visible	Capybaras and donkeys are the only species detected.
[3]	2021	Animal Classification and Detection	DCNN	Camera-trap images	Visible and Thermal	Performance is superior to that of ML algorithms.
[1]	2020	Animal Detection and Classification	CNN	Elephant & Cheetah	RGB	Infrared images are not accepted as input.
[11]	2020	Object Recognition	CNN	BCMOTI, Snapshot Wisconsin	Visible and Thermal	Training with more images will improve image quality.
[17]	2019	Animal Classification	MP-CNN, MHKC, FVSAE	ImageNet	Visible and Thermal	The misclassification rate is high compared to New Images.
[18]	2019	Animal Classification and Detection	DNN, MB-LBP, Movidius NCS, AdaBoost, Classifier.	AlexNet	RGB	This system does not employ thermal imaging. Only GPU and TPU systems are supported.
[14]	2019	Animal Recognition	CNN, Binary, and Multi classification	Camera	RGB and Thermal	The dataset contains a minimum number of images.
[15]	2019	Animal Detection	DCNN	Camera Trap Images	Visible & thermal	ImageNet ILSVRC classification that has been pretrained
[19]	2018	Animal Detection	DWA	Thermal Camera	Thermal Image	This system makes no allowance for visible images.

IV. CONCLUSION

This review has to address a lot of concerns in order to create an effective algorithm for animal identification and categorization. The taxonomy of animals and methods of animal detection are the subject of several scientific investigations. One of the most well-known and impressive machine learning techniques, deep learning has produced ground-breaking results in a wide range of applications. Convolutional neural networks employ numerous levels of processing to create representations that may be used to solve challenging problems. In this research, we examine and compare the shortcomings of more than 25 studies that used learning algorithms to identify and categorise animals. In addition to highlighting the main problems and difficulties.

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