ABSTRACT

Efficient and reliable monitoring of wild animals in their natural habitats is essential to inform conservation and management decisions. Visual animal biometrics is rapidly gaining popularity as it enables a non-invasive and cost-effective approach for wildlife monitoring applications. Wide spread of camera traps led to large volumes of collected wildlife pictures inexpensively, unobtrusively, and frequently. However, extracting information from these pictures remains an expensive, time-consuming, manual task making it hard to manage. Based on the recent advances in deep learning techniques, we propose in this paper a framework to build automated animal recognition in the wildlife, we demonstrate that such information can be automatically extracted by deep learning, a cutting-edge type of artificial intelligence. In order to automate the detection process while retaining robustness to blur, partial occlusion, illumination and pose variations, we use the recently proposed Faster-RCNN object detection framework to efficiently detect animals in images. We then compare this method with Convolution Neural Networks (CNN) method to evaluate the overall recognition accuracy of animals from the images. For the experiments, the database of wild animals is created. The overall performances were obtained using different number of training images and test images. Those efficiency gains immediately highlight the importance of using deep neural networks to automate data extraction from camera-trap images. Our results suggest that this technology could enable the inexpensive, unobtrusive, high-volume, and even real-time collection of a wealth of information about vast numbers of animals in the wildlife.

Keywords: Neural Network, Deep Learning, CNN, Inception model, Faster RCNN, SoftMax

LIST OF FIGURES

| Fig No. | Figure Name | Page No. |
|---------|--|----------|
| 1.1 | Overview of Animal Classification | 1 |
| 1.2 | Animal Recognition System | 2 |
| 4.1 | System Architecture | 14 |
| 4.2 | Use Case Diagram | 15 |
| 4.3 | Sequence Diagram | 16 |
| 4.4 | Collaboration Diagram | 17 |
| 4.5 | State Chart Diagram | 17 |
| 4.6 | Activity Diagram | 18 |
| 4.7 | Deployment Diagram | 18 |
| 5.1 | Convolution Operation | 23 |
| 5.2 | ReLU Operation | 23 |
| 5.3 | Max Pooling Operation | 24 |
| 5.4 | Design of Convolutional Neural Network | 24 |
| 5.5 | Architecture of GoogLeNet | 25 |
| 5.6 | Faster RCNN Operation | 26 |
| 5.7 | The Architecture of Faster RCNN | 27 |
| 5.8 | Anchors for an image | 28 |
| 5.9 | Region Proposal Network Operation | 29 |
| 5.10 | Regions of Interest Operation | 29 |
| 6.1 | Training and Validation Accuracy for CNN | 31 |
| | algorithm | |
| 6.2 | Training and Validation Loss for CNN algorithm | 31 |

LIST OF TABLES

| Table No. | Table Name | Page No. |
|-----------|---------------------------------------|----------|
| 5.1 | Different Filters | 22 |
| 5.2 | Parameters for GoogLeNet Architecture | 25 |
| 6.1 | Comparison of different algorithms | 32 |
| 7.1 | Test Report | 36 |

CONTENTS

| ABSTRACT | |
|-----------------------------------|----|
| LIST OF FIGURES | |
| LIST OF TABLES | |
| CHAPTER 1 INTRODUCTION | 1 |
| CHAPTER 2 LITERATURE SURVEY | 3 |
| CHAPTER 3 SYSTEM ANALYSIS | 7 |
| 3.1 Problem Definition | 7 |
| 3.2 Existing System | 7 |
| 3.3 Proposed System | 8 |
| 3.4 Requirement Analysis | 8 |
| 3.4.1 Functional Requirements | 8 |
| 3.4.2 Non-Functional Requirements | 10 |
| 3.5 Feasibility Study | 10 |
| 3.5.1 Technical Feasibility | 11 |
| 3.5.2 Economic Feasibility | 11 |
| 3.5.3 Social Feasibility | 11 |
| 3.6 Software Analysis | 11 |
| 3.6.1 Hardware Requirements | 12 |
| 3.6.2 Software Specifications | 12 |
| | |
| CHAPTER 4 SYSTEM DESIGN | 13 |
| 4.1 System Architecture | 13 |

| 4.2 UML Diagrams | 14 |
|--|----------|
| 4.2.1 Use Case Diagram | 15 |
| 4.2.2 Sequence Diagram | 16 |
| 4.2.3 Collaboration Diagram | 17 |
| 4.2.4 State Chart Diagram | 17 |
| 4.2.5 Activity Diagram | 18 |
| 4.2.6 Deployment Diagram | 18 |
| 4.3 Keras and Tensorflow | 19 |
| 4.3.1 Keras | 19 |
| 4.3.2 Tensorflow | 20 |
| CHAPTER 5 SYSTEM IMPLEMENTATION | 21 |
| 5.1 Design Considerations | 21 |
| 5.2 Description of Proposed Algorithm | 21 |
| 5.2.1 Input Image | 21 |
| 5.2.2 Image Classification using CNN | 21 |
| 5.2.3 Image Classification using FRCNN | 26 |
| 5.2.4 Output | 30 |
| CHAPTER 6 EXPERIMENT RESULTS AND EVALUATIONS | 31 |
| CHAPTER 7 TESTING | 33 |
| 7.1 Introduction | 33 |
| 7.2 Testing Objectives | 33 |
| 7.3 Testing Procedures | 33 |
| 7.4 Test Report CHAPTER 8 CONCLUSION AND FUTURE SCOPE | 36 38 |

CHAPTER 1 INTRODUCTION

Having an updated knowledge about different animals will impact our study in managing species in the ecosystem. Identifying animals and their features manually remains a manual and expensive, time-consuming task. Thus, we propose that such identification and classification can be done with utmost accuracy using deep learning neural network techniques. The main purpose of using deep learning neural network techniques is that a neural network framework can automatically learn from the training images by extracting features from the images and predicts the test images with efficient accuracies. This intends to reduce the manual effort and cost and to maintain and conserve the wildlife ecosystem. We will demonstrate that such detection of animal can be done by deep convolution neural network frameworks with high accuracies.



Figure 1.1: Overview of Animal Classification

Data Mining is the process of identifying and discovering trends and patterns in the large sets of data which is a combination of multiple fields that include machine learning, statistics and database systems. It focuses on extracting information from the large sets of data and transforming into a interpretable and comprehensible format for the future use. It is mainly used for data pre-processing, data classification and categorization.

Image Classification analyses, identifies and discover several properties of an image and organizes the image data into various categories using several algorithms. It mainly employs two characteristic phases of processing: training and testing. In the training phase, a unique

identity of each category is obtained. In the testing phase, these unique identities are used to classify the image data into categories.

A neural network is a series of algorithms that analyses a set of data and recognizes the underlying relationships within the data. They are the workhorses of deep learning.

Deep Learning is an artificial intelligence technology that is used for processing larger sets of data and mainly used in decision making and image classification and pattern creation. It is a subset of

Machine Learning that comprises of networks capable of training by unsupervised learning from the unstructured data. The reason why we choose to use deep learning is that it is one of that only methods that can overcome the challenges of feature extraction by learning several different features itself from the large sets of data without much effort from the programmer.

Generally, in a recognition system, when an input image is provided, features are extracted from the image. These are used by the network to train itself from the training data and organizes the data into classes. The gained knowledge from the training is used in predicting the test data based on the features and classifies them accordingly. A recognition system can be employed with identification and verification. Identification is where the given image is compared with all the other images and produces a ranked list of matches while the Verification is where the given image is compared, and the identity of the animal is confirmed or denied.



Figure 1.2: Animal Recognition System

CHAPTER 2

LITERATURE SURVEY

This chapter gives the overview of literature survey. This chapter represents some of the relevant work done by the researchers.

Many existing techniques have been studied by the researchers on Animal Classification problem, few of them are discussed below.

Animal Detection Using Deep Learning Algorithm

Prakash, Banupriya, First International Conference on Intelligent Digital Transformation ICIDT – 2019

Efficient and reliable monitoring of wild animals in their natural habitat is essential. This project develops an algorithm to detect the animals in wild life. Since there are large number of 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.

Animal recognition system based on convolutional neural network

Trnovszky, Tibor & Kamencay, Patrik & Orješek, Richard & Benco, Miroslav & Sykora, Peter. (2017). Animal Recognition System Based on Convolutional Neural Network. Advances in Electrical and Electronic Engineering. 15. 10.15598/aeee.v15i3.2202.

The author studied the performances of well-known image recognition methods such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Local Binary Patterns Histograms (LBPH) and Support Vector Machine (SVM) are tested and compared with proposed convolutional neural network (CNN) for the recognition rate of the input animal images. Their experiments, the overall recognition accuracy of PCA, LDA, LBPH and SVM is demonstrated. Next, the time execution for animal recognition process is evaluated. The all experimental results on created animal database were conducted. This created animal database consist of 500 different subjects (5 classes/ 100 images for each class). The experimental result shows that the PCA features provide better results as LDA and LBPH for large training set. On the other hand, LBPH is better than PCA and LDA for small training data set. For proposed CNN we have obtained a recognition accuracy of 98%. The proposed method based on CNN outperforms the state of the art methods.

Object detection with discriminatively trained part-based models.

P. F. Felzenszwalb, R. B. Girshick, D. McAllester and D. Ramanan, "Object Detection with Discriminatively Trained Part-Based Models," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 32, no. 9, pp. 1627-1645, Sept. 2010.

We describe an object detection system based on mixtures of multiscale deformable part models. Our system is able to represent highly variable object classes and achieves state-of-the-art results in the PASCAL object detection challenges. While deformable part models have become quite popular, their value had not been demonstrated on difficult benchmarks such as the PASCAL data sets. Our system relies on new methods for discriminative training with partially labeled data. We combine a margin-sensitive approach for data-mining hard negative examples with a formalism we call latent SVM. A latent SVM is a reformulation of MI--SVM in terms of latent variables. A latent SVM is semiconvex, and the training problem becomes convex once latent information is specified for the positive examples. This leads to an iterative training algorithm that alternates between fixing latent values for positive examples and optimizing the latent SVM objective function.

Accurate wild animal recognition using PCA

P. Kamencay, T. Trnovszky, M. Benco, R. Hudec, P. Sykora and A. Satnik, "Accurate wild animal recognition using PCA, LDA and LBPH," 2016 ELEKTRO, Strbske Pleso, 2016, pp. 62-67.

The author studied performances of image recognition methods such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Local Binary Patterns Histograms (LBPH) are tested and compared for the image recognition of the input animal images. The main idea of this paper is to present an independent, comparative study and some of the benefits and drawbacks of these most popular image recognition methods. Two sets of experiments are conducted for relative performance evaluations. In the first part of our experiments, the recognition accuracy of PCA, LDA and LBPH is demonstrated. The overall time execution for animal recognition process is evaluated in the second set of our experiments. We conduct tests on created animal database. The all algorithms have been tested on 300 different subjects (60 images for each class). The experimental result shows that the PCA features provide better results as LDA and LBPH for large training set. On the other hand, LBPH is better than PCA and LDA for small training data set.

Wild Animal Detection Using Deep Convolutional Neural Network

Verma, Gyanendra & Gupta, Pragya. (2018). Wild Animal Detection Using Deep Convolutional Neural Network. 10.1007/978-981-10-7898-9_27.

Wildlife monitoring and analysis are an active research field since last many decades. In this paper, we focus on wildlife monitoring and analysis through animal detection from natural scenes acquired by camera-trap networks. The image sequences obtained from camera-trap consist of highly cluttered images that hinder the detection of animal resulting in low-detection rates and high false discovery rates. To handle this problem, we have used a camera-trap database that has candidate animal proposals using multilevel graph cut in the spatiotemporal domain. These proposals are used to create a verification phase that identifies whether a given