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Wild Animal Detection Using CNN

Dr R. Kavitha[1], Niranjana Devi. S[2], Amirthakarthiga. N[3], Srivarshini R[4]
[1, 2, 3, 4]*Department of Computer Science and Engineering, Kalasalingam Academy of Research and Institution Anand Nagar, Krishnankoil, Tamilnadu.*

Abstract: Efficient and reliable monitoring of wild animals in their natural habitats is essential to inform conservation and management decisions. Automatic covert cameras or "camera traps" are being an increasingly popular tool for wildlife monitoring due to their effectiveness and reliability in collecting data of wildlife unobtrusively, continuously and in large volume. However, processing such a large volume of images and videos captured from camera traps manually is extremely expensive, time-consuming and also monotonous. This presents a major obstacle to scientists and ecologists to monitor wildlife in an open environment. Leveraging on recent advances in deep learning techniques in computer vision, we propose in this paper a framework to build automated animal recognition in the wild, aiming at an automated wildlife monitoring system. In particular, we use a single-labeled dataset from Wildlife Spotter project, done by citizen scientists, and the state-of-the-art deep convolutional neural network architectures, to train a computational system capable of filtering animal images and identifying species automatically. Our experimental results achieved an accuracy at 96.6% for the task of detecting images containing animal, and 90.4% for identifying the three most common species among the set of images of wild animals taken in South-central Victoria, Australia, demonstrating the feasibility of building fully automated wildlife observation. This, in turn, can therefore speed up research findings, construct more efficient citizen science based monitoring systems and subsequent management decisions, having the potential to make significant impacts to the world of ecology and trap camera images analysis.

Keywords: Convolutional Neural Network (CNN), unobtrusively. Single-labeled dataset, species, wild animals

I. INTRODUCTION

Observing wild animals in their natural environments is a central task in ecology. The fast growth of human population and the endless pursuit of economic development are making over-exploitation of natural resources, causing rapid, novel and substantial changes to Earth's ecosystems. An increasing area of land surface has been transformed by human action, altering wildlife population, habitat and behavior. More seriouslymany wild species on Earth have been driven to extinction, and many species are introduced into new areas where they can disrupt both natural and human systems. Monitoring wild animals, therefore, is essential as it provides researchers evidences to inform conservation and management decisions to maintain diverse, balanced and sustainable ecosystems in the face of those changes. Various modern technologies have been developed for wild animal monitoring, including radio tracking , wireless sensor network tracking , satellite and global positioning system (GPS) tracking , and monitoring by motion sensitive camera traps .

Motion-triggered remote cameras or "camera traps" are an increasingly popular tool for wildlife monitoring, due to their novel features equipped, wider commercial availability, and the ease of deployment and operation. For instance, a typical covert camera model is capable of not only capturing high definition images in both day and night, but also collecting information of time, temperature and moon phase integrated in image data. In addition, generous and flexible camera settings allow tracking animals secretly and continuously. Once being fully charged, a camera can snap thousands of consecutive images, providing a large volume of data. These specifications make camera traps a powerful tool for ecologists as they can document every aspect of wildlife.

Visual data, if can be captured, is a rich source of information that provide scientists evidences to answer ecology-related scientific questions such as: what are the spatial distributions of rare animals, which species are being threatened and need protection such as bandicoot, which cohort of pest species, such as red fox and rabbit, need to be controlled; these are examples of key questions to understand wild animals' populations, ecological relationships and population dynamics. To this end, a recently widely-used approach by ecologists is to set up several camera traps in the wild to collect image data of wild animals in their natural habitats.

Camera trapping is rapidly being adopted for wildlife monitoring thanks to advances in digital technology that produce more modern camera traps with automation of system components but lower cost of purchase; the task of analyzing huge collections of camera trap images, however, has been conducted manually. Despite the fact that human visual system can process images effortlessly and rapidly, processing such an enormous number of images manually is much expensive.

For example, to date, the Snapshot Serengeti project1 gathered 3.2 million images through 225 camera traps across the Serengeti National Park, Tanzania from 2010–2013 Another similar project, Wildlife Spotter2, collected millions photos of wildlife captured in tropical rainforests and dry rangelands of Australia. Unfortunately, due to automatic trap camera snapping mechanism, the vast majority of captured images are challenging to process, even for human. Only a limited number of collected images are in favorable condition.

Many images contain only partial body of animal objects , in others the animal objects are captured in the whole body but too far from camera (Figure 2b), in varied views or deformations , or occlusion . Furthermore, numerous images are in grayscale as they were captured at night with infrared flash support , and a large number of images contains no animal (75% of the Snapshot Serengeti and 32.26% of Wildlife Spotter labeled images were classified as "no animal"), while in others might appear several objects belonging to different species. Overwhelming amounts of data and limited image quality, therefore, remarkably slow down the image analyzing process.

In this paper, we design a framework for animal recognition in the wild, aiming at a fully automatic wildlife spotting system. Our work is motivated by the state-of-the-art power of recent deep CNN models for image classification, in particular the recent evidence that automated recognition can surpass human at certain object recognition tasks in the Image Net competition. We carry out experiments on datasets of Wildlife Spotter project, containing a large number of images taken by trap cameras set up by Australian scientists. More specifically, since the Wildlife Spotter dataset includes both animal and non-animal images, we divide the wild animal identifying automation into two subsequent tasks: (1) Wildlife detection, which is actually a binary classifier capable of classifying input images into two classes: "animal" or "no animal" based on the prediction of animal presence in images; and (2) Wildlife identification, a multiclass classifier to label each input image with animal presence by a specified species. The core of each task is essentially a deep CNN-based classifier, trained from prepared datasets manually labeled by volunteers. Several selected deep CNN architectures are employed to the framework for comparisons. The success of Task 1 will have a significant impact in improving the efficiency of citizen science-based projects (e.g., Wildlife Spotter) by automatically filtering out a large portion of non-animal images where citizen annotators are currently wasting their time on.

Our experimental results on the Wildlife Spotter datasets show that this approach is feasible, and can save considerable time and expense. Hence, the key contribution of this work is that, with sufficient data and computing infrastructure, deep learning could be employed to build a fully automatic image classification system at large scale, liberating scientists from the burden of manual processing of millions of images, which is considered by the project managers "It's a job that computers just can't do"3. In addition, our proposed framework can be combined with the existing citizen science project, forming a "hybrid" image classifier whose automated component works as a recommendation system, providing volunteers remarkable suggestions to speed up their classifying decisions.

II. LITERATURE REVIEW

1) Energy Reduction Methods for Wild Animal Detection Devices, The proposed methods are sensitivity adjustment for the motion sensor, attachment of a hat, motion detection by a frame difference method, and separation of functions on the device. The sensitivity adjustment for the motion sensor reduces the number of taking images by the camera. The attachment of a hat reduces the number of sensings by the motion sensor. The frame difference method reduces the number of inferences by deep learning. The separation of functions on the device reduces the power consumption in both operation time and idle time. In the experiments, we evaluate the effect of the proposed four methods by applying them to a wild animal detection device which we proposed previously. We compare the energy reduction ratio when each method is applied and all methods are combined.
2) Multifeature-Based Surround Inhibition Improves Contour Detection in Natural Images,The main contribution is the multifeature-based centersurround framework, in which the surround inhibition weights of individual features, including orientation, luminance, and luminance contrast, are combined according to a scale-guided strategy, and the combined weights are then used to modulate the final surround inhibition of the neurons. The performance was compared with that of single-cue-based models and other existing methods (especially other biologically motivated ones). The results show that combining multiple cues can substantially improve the performance of contour detection compared with the models using single cue. In general, luminance and luminance contrast contribute much more than orientation to the specific task of contour extraction, at least in gray-scale natural images
3) Dynamical Characteristics of Wild-Type Mouse Spontaneous Pupillary Fluctuations,Properties of pupillometry dynamics, such as determinism, were previously investigated for healthy human subjects; however, the dynamical characteristics of pupillometry data in mouse models, and whether they are similar to those of human subjects, remain largely unknown.

Therefore, it is necessary to establish a thorough understanding of the dynamical properties of mouse pupillometry dynamics and to clarify whether it is similar to that of humans. In this study, dynamical pupillometry characteristics from 115 wildtype mouse datasets were investigated by methods of nonlinear time series analysis. Results clearly demonstrated a strong underlying determinism in the investigated data. Additionally, the data's trajectory divergence rate and predictability were estimated

4) Contrast enhanced magneto-motive ultrasound in lymph nodes - modelling and pre-clinical imaging using magnetic microbubbles, The feasibility of the proposed application was explored using a combination of pre-clinical ultrasound imaging and finite element analysis. First, contrast enhanced ultrasound imaging on one wild type mouse recorded lymphatic drainage of magnetic microbubbles after bolus injection. Second, preliminary CE-MMUS data were acquired as a proof of concept. Third, the magneto-mechanical interactions of a magnetic microbubble with an elastic solid were simulated using finite element software. Accumulation of magnetic microbubbles in the inguinal lymph node was verified using contrast enhanced ultrasound, with peak enhancement occurring 3.7 s post-injection. Preliminary CE-MMUS indicates the presence of magnetic contrast agent in the lymph node. The finite element analysis explores how the magnetic force is transferred to motion of the solid, which depends on elasticity and bubble radius, indicating an inverse relation with displacement. Combining magnetic microbubbles with MMUS could harness the advantages of both techniques, to provide perfusion information, robust lymph node delineation and characterisation based on mechanical properties.
5) Automatic detection of moving wild animals in airborne remote sensing images,Thus, it is expected to estimate population densities of large-sized mammals using remote sensing. However it costs hard labor to find directly wild animals by visual examination of remote sensing images. In addition, we may overlook some wild animals because remote sensing image is taken from above, not from side. To solve these problems we developed an algorithm for automatic detection of moving wild animals in the snow in airborne remote sensing images with 60 % overlap.

III. METHODOLOGY

A. Convolutional Neural Network

A Convolutional Neural Network, also known as CNN or ConvNet, is a class of neural networks that specializes in processing data that has a grid-like topology, such as an image. A digital image is a binary representation of visual data. It contains a series of pixels arranged in a grid-like fashion that contains pixel values to denote how bright and what color each pixel should be implemented. The human brain processes a huge amount of information the second we see an image. Each neuron works in its own receptive field and is connected to other neurons in a way that they cover the entire visual field. Just as each neuron responds to stimuli only in the restricted region of the visual field called the receptive field in the biological vision system, each neuron in a CNN processes data only in its receptive field as well. The layers are arranged in such a way so that they detect simpler patterns first (lines, curves, etc.) and more complex patterns (faces, objects, etc.) further along by using a CNN. In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on the shared-weight architecture of the convolution kernels that shift over input features and provide translation equivariant responses. Counter-intuitively, most convolutional neural networks are only equivariant, as opposed to invariant, to translation. They have applications in image and video recognition, recommender systems, image classification, image segmentation, medical image analysis, natural language processing, brain-computer interfaces, and financial time series. Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field. Convolutional Neural Network Architecture A CNN typically has three layers: a convolutional layer, a pooling layer, and a fully connected layer.

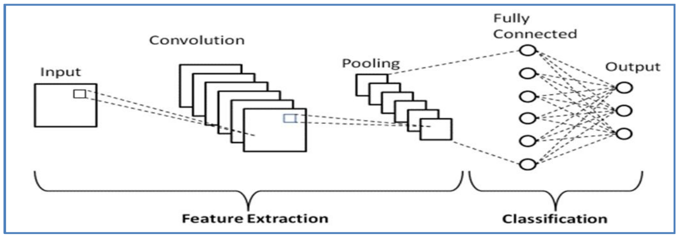

Fig1. Architecture of CNN

B. Matlab

MATLABis a high-level language and interactive environment for numerical computation, visualization, and programming. Using MATLAB, you can analyze data, develop algorithms, and create models and applications. The language, tools,and built-in math functions enableyou to explore multiple approaches and reach a solution faster than with spread sheets or traditional programming languages, such as C/C++ or Java You can use MATLAB for arange of applications, including signal processing and communications, imageand video processing, control systems, test and measurement, computational finance, and computational biology. More than a million engineers and scientists inindustry and academia use MATLAB,the language of technical computing.

VISUALIZING DATA

MATLAB provides built-in 2-D and 3-D plotting functions, as well as volume visualization functions. You can use these functions to visualize and understand data and communicate results. Plots can be customized either interactively or programmatically. The MATLAB plot gallery provides examples of many waysto display data graphically in MATLAB. For each example, you can view and download source code to use inyour MATLAB application.

C. Proposed System

In this section, we present our proposed image classification framework and its application to the Wildlife video datasets. First we describe the datasets. Then we introduce a CNN based framework for wildlife identification.

First we have to collect the data video or input video of the wild animal,next, we construct two settings to apply our proposed framework on two tasks: Wildlife detection and Wildlife identification.

It has been shown that CNNs outperform other approaches in the topic of image classification; thus in this work we focus on adopting recent state-of-the-art CNN architectures for both those two tasks – detection and recognition. Finally,we characterize selected CNN architectures employed in our experiments and implementations.

ADVANTAGES

Efficient and reliable monitoring of wild animals in their natural habitats is essential to inform conservation and management decisions.

It do not require human supervision for the task of identifying important features.

It is very accurate at image recognition and classification.

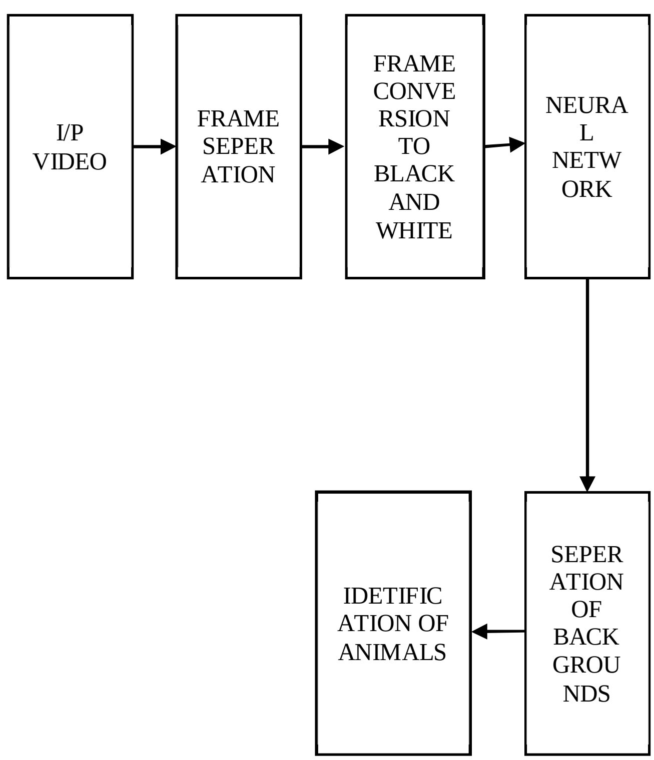

Fig2. Block diagram of Proposed System

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. I/P Video

Firstly, we get input from the outside for which we get the wild life video which is captured by the camera. Here the data is collected as video which is then transferred to the preprocessing.

B. Frame Seperation

Secondly, we have to separate the frames the input video which is captured in the wildlife contains both animal and non-animal images with proportions of 67.74% and 32.26%, respectively.so that we have separate the frame by Wildlife detection to specify whether there exist animal in an image, and Wildlife identification to identify which species the animal objects belong to.

C. Frame Conversion To Black And White Images

If the frame is separated then we have convert the color of the image. The input image is in RGB color which is Red, Green and Yellow .the color of the RGB image is converted into black and white image or gray scale image using color conversion.

D. Neural Network

Next the color converted image is transferred to the convolutional neural network algorithm. In convolutional neural network we eliminate the noises and error occurs in the images. By which we get the error free image to detect wild animals.

E. Seperation Of Backgrounds

The error free image is then converted to K-Means segmentation was successful enough to bring in a differentiating factor between the images as it was able to remove the background of the images leaving behind the animals in the images. Finally we identify the animals through CNN which is more accurate and the proposed system is easy to implement.

Fig3. Animal Detected (1)

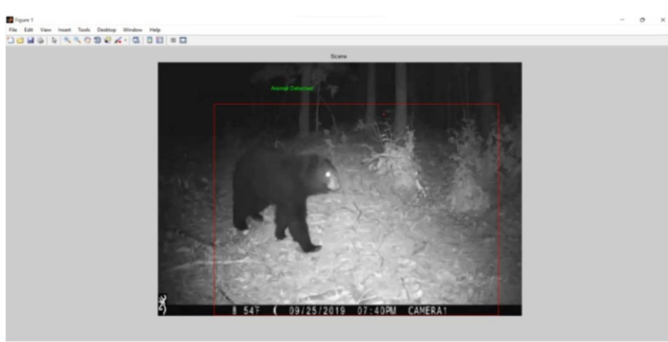

Fig4. Animal Detected (2)

V. CONCLUSION

In this paper, using the Wildlife Spotter dataset, which contains a large number of images taken by trap cameras in South-central Victoria, Australia, we proposed and demonstrated the feasibility of a deep learning approach towards constructing scalable automated wildlife monitoring system.

Our models achieved more than 96% in recognizing images with animals and close to 90% in identifying three most common animals (bird, rat and bandicoot). Furthermore, with different experimental settings for balanced and imbalanced, the system has shown to be robust, stable and suitable for dealing with images captured from the wild. We are working on alternative ways to improve the system's performance by enhancing the dataset, applying deeper CNN models and exploiting specific properties of camera trap images. Towards a fully automated wild animal recognition system, we would investigate transfer learning to deal with problem of highly imbalanced data. In the near future, we focus on developing a "hybrid" wild animal classification framework whose automated module working as a recommendation system for the existing citizen science-based Wildlife Spotter project.

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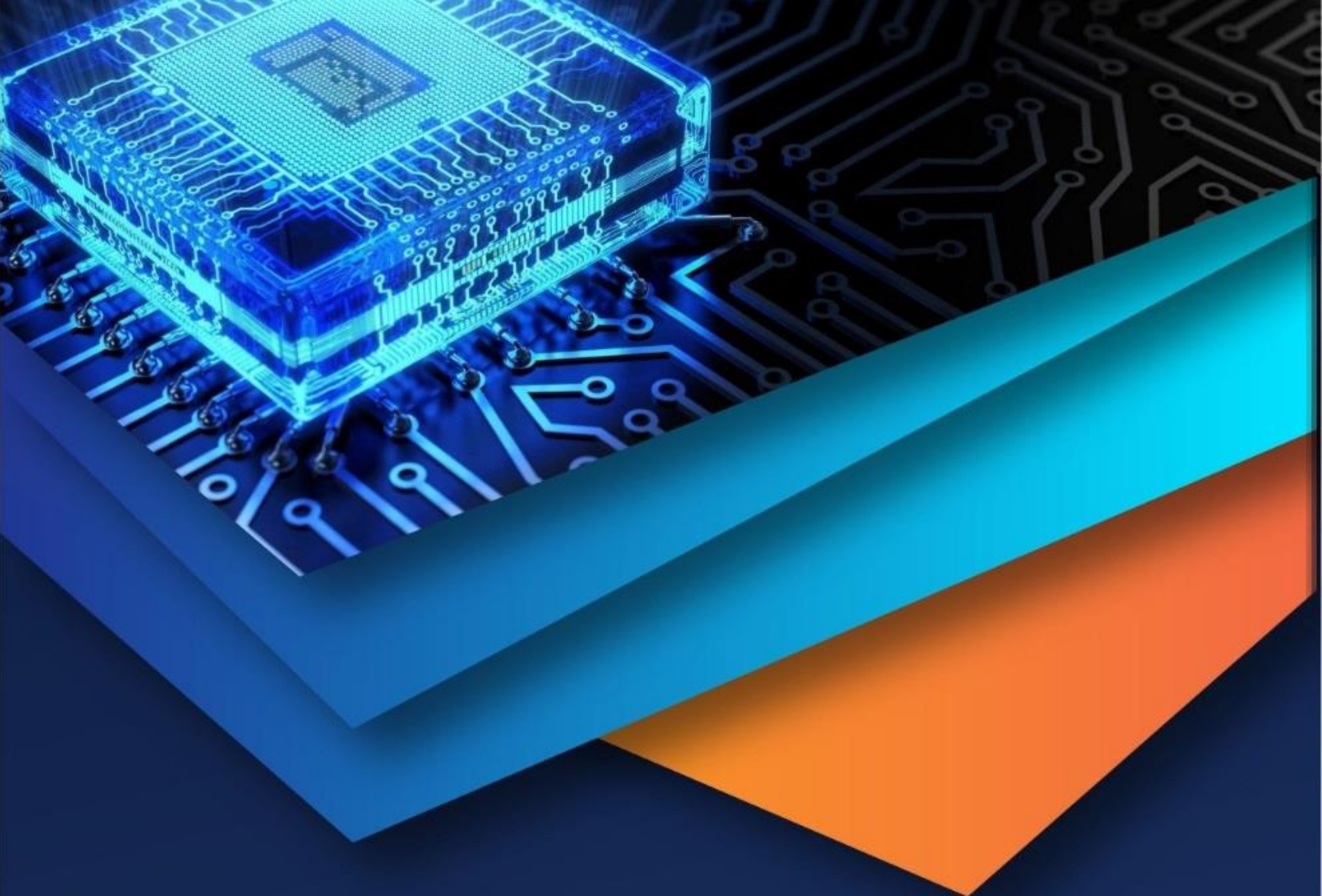

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