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Machine Learning Algorithms for Automated Image Capture and Identification of Fall Armyworm (FAW) Moths

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Automated entomology is one of the field that has received a fair attention from the computer scientists and its support disciplines. This can further be confirmed by the recent attention that the Fall Armyworm (FAW) (Spodoptera frugiperda) has received in Africa particularly the Southern African Development Community (SADC). As the FAW is known for its devastating effects, stakeholders such as the Food and Agriculture Organization (FAO), SADC and University of Zambia (UNZA) have agreed to develop a robust early monitoring and warning system. To supplement the stakeholders' efforts, we choose a branch of artificial intelligence that employs deep neural network architectures known as Google TensorFlow. It is an advanced state-of-the-art machine learning technique that can be used to identify the FAW moths. In this paper, we use Google TensorFlow, an open source deep learning software library for defining, training and deploying machine learning models. We use the transfer learning technique to retrain the Inception v3 model in TensorFlow on the insect dataset, which reduces the training time and improve the accuracy of FAW moth identification. Our retrained model achieves a train accuracy of 57 – 60 %, cross entropy of 65 – 70% and validation accuracy of 34 – 50%.

Keywords— Fall Armyworm, Machine Learning, Convolutional Neural Network, FAW Identification, TensorFlow, Inception v3

I. INTRODUCTION

According to [1], the health and well-being of humans can be impacted in a positive and negative sense by insects if not monitored and controlled therefore these ecosystem creatures deserve to be understood. The understanding of insects and their relationship to humans, the environment, and other organisms is called entomology. Entomology has made great contributions to such diverse fields as agriculture, biology, human/animal health, and forensics.

One of the insect attracting a lot of studies in Africa and the Southern African Development Community (SADC) in particular is the Fall Armyworm (FAW) (Spodoptera frugiperda) [1] – [3]. According to [2], the FAW is a moth that is indigenous throughout America where it is widely agreed to be one of the most damaging crop pests. It attacks more than 80 different plant species, including maize, a major staple food in sub-Saharan Africa on which more than 200 million people depend [1]. The FAW outbreak was first recorded in January 2016 [2]. The FAW can be one of the most difficult to control especially when it has reached an advanced larval development stage. It can cause extensive crop losses of up to 73% depending on existing conditions.

The FAW has a life cycle of about 30 days (at a daily temperature of ~28°C) during the warm summer months and may extend to 60-90 days in cooler temperatures [1], [2], [3]. The FAW moths are migratory in nature and can fly for over 100km per night. The female moths can lay an average of 1500 eggs and can produce multiple generations very quickly without pause in tropical environments [1]-[4]. With the aforementioned, noticing the presence of the FAW at an early stage can minimize economic hardship that this pest can cause. To achieve this, we use Machine Learning (ML) a subfield of soft computing within computer science that studies the design of algorithms that can learn.

ML has a subfield called deep learning that is inspired by artificial neural networks. Inside deep learning, there is a specific kind of neural network called the convolutional neural network, also commonly referred to as CNN or ConvNet. [1]. The CNN neurons are inspired by the organization of human visual cortex. It's a multi-layer perceptron and a feed-forward neural network which has been found to be effective in image recognition. In CNN, an input image is passed through the network layers and compared piece by piece. These pieces are called features. For each training image, filters are applied at different resolution at each layer and a convolved image is outputted. The convolved image is used as an input to the next layer and so on. The filters may include simple features such as brightness and edges. The filters may increase in complexity as the object progress from layer to layer.

TensorFlow is an open source software library for high performance numerical computation [5]. Its flexible architecture allows easy deployment of computation across a variety of platforms (CPUs, GPUs, TPUs), and from desktops to clusters of servers to mobile and edge devices [6]. As a Google Brain team within Google's AI organization, TensorFlow comes with strong support for machine learning and deep learning including fields such as speech recognition, computer vision, robotics, information retrieval, information extraction, natural language processing, drug testing and across many other scientific domains [5],[6].

In this paper, we use the transfer learning technique to retrain the Inception v3 model in TensorFlow on the insect dataset, which reduces the training time and improve the accuracy of insect identification. We use two (2) classes to identify the insects namely the FAW and others.

This paper is structured as follows: Section II devoted to literature review, Section III describes the proposed Inception V3 model in Tensorflow, Section IV is the experiment while Section V discusses the experiment results and finally, Section VI provides some conclusion.

II. LITERATURE REVIEW

The current approaches to image identification make essential use of machine learning methods and convolutional neural network is amongst the newest approach. This approach is being used by researcher in various image problems such as identification, classification and recognition.

In [7], CNN is used to detect skin cancer automatically by classifying skin images. The work was tested on standard cancer dataset and obtained more than 85% accuracy. In [8], CNN is used to classify insects using hierarchical architecture called Hierarchical Deep convolutional neural network. The test was done on 217,657 insect images from 277 unique classes. The outcome was a top-5 misclassification rate of 22.54% and a top-10 misclassification rate of 14.01%.

Tomato whitefly and its predatory bugs are detected using CNN in [9] and weighted averaged accuracy for deep learning detected insects achieved was 87.4%. In [10], a CNN-based system for small objects identification was used and extended to identify intra-class variation in whiteflies that affect tomato plants and experimental results showed outstanding performance on whiteflies dataset.

In [11], an algorithm called Simultaneous Detection and Segmentation (SDS) was proposed to detect all instances of a category in an image and correctly mark each instance that belonged to that category. The algorithm required segmentation of individual object instances and bounding box detection. It also used CNN to extract features on each region and trained a Support Vector Machine (SVM) on top of the CNN features to assign a score for each category to each candidate. The results of the study showed a 5 point boost (10% relative) over state-of-the-art on semantic segmentation, and state-of-the-art performance in object detection.

In [12], an automatic detection pipeline based on deep learning for identifying and counting pests images taken inside field traps was proposed. It used a sliding window based detection pipeline and applied CNN on the image patches at different locations to determine the probability of containing a specific pest type. Image patches were then filtered by non-maximum suppression and thresholding, according to their locations and associated confidences, to produce the final detections. Qualitative and quantitative experiments demonstrated the effectiveness of the proposed method on a codling moth dataset.

Based on Inception-v3 model in TensorFlow platform, the transfer learning technology was used to retrain the animal category datasets, which improved the accuracy of animal classification [13]. After giving a random image input of tiger, the Inception v3 model evaluation time was 2.160 seconds and the model accuracy was above 97 %.

In [14], TensorFlow platform was used to implement recognition of a particular vegetable which made use of OpenCV as the main library database. The experimental results showed an accuracy of 99 % of identifying vegetables. In [15] and [16], artificial intelligence technologies are used in digital identity management system implementation based on user credentials. This study will apply similar technologies in the identification of FAW.

III. INCEPTION-V3 MODEL IN TENSORFLOW

Inception v3 is a widely-used image recognition model that has been shown to attain greater than 78.1% accuracy on the ImageNet dataset. The model is the culmination of many ideas developed by multiple researchers over the years. Its uses the Transfer learning machine learning method which utilizes a pre-trained neural network. The model consist of two parts.

A. *Feature extraction part with a convolutional neural network.*

B. *Classification part with fully-connected and softmax layers.*

The pre-trained Inception-v3 model achieves state-of-the-art accuracy for recognizing general objects. The model extracts general features from input images in the first part and classifies them based on those features in the second part as shown in fig. 1.

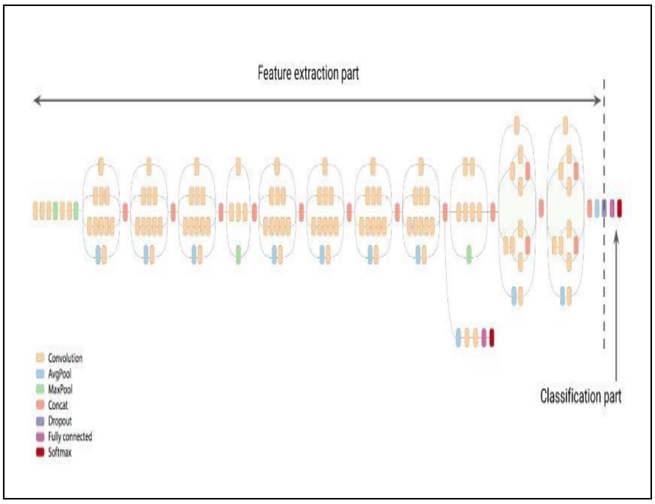

Fig. 1. A high-level diagram of the Inception model. Source [16].

IV. EXPERIMENT

To successfully conduct this experiment, the following software, hardware and setup was used:

A. *Software*

We used Ubuntu 16.04 (64-bit), python 2.7.11+, pip 18.1, virtualenv 16.2.0 and tensorflow 1.12.0.

B. *Hardware*

The laptop used was an HP Probook 4740s which had an Intel(R) Core(TM) i5-2450M CPU @ 2.50GHz processor with 2nd Generation Core Processor Family Integrated Graphics Controller 64 bits @ 33MHz 32MB.

C. *Setup*

This experiment was setup for FAW moth identification using Inception-v3 on Tensor Flow framework using the following steps.

1) *Step 1.Training set*

A total of 100 images were compiled as the training dataset for this experiment. The first half of this dataset was captured from the traps currently installed at Liempa farm within the UNZA with unconstrained pose settings while the other half was downloaded from the internet. The unconstrained pose settings induced variability in orientation of the individual moth. This dataset was used as input to the machine learning model in which retraining was provided based upon pre-trained inception v3 algorithm. The images were of different sizes but we managed to stay between 50 x 50 pixels and 4000 x 4000 pixels

The training dataset folder was called training_images and had two sub categories namely FAW and others. FAW contained the FAW moth images and others contained other insects.

2) *Step 2. Test set.*

A total of 10 images were compiled as the test dataset for this experiment. The test dataset folder was called test_images and it had no subcategories.

3) *Retraining and fine-tuning the model*

We retained the parameters of the previous layer like it was done in [11] and only changed the last layer which was then fed with the dataset to retrain it. The output layer also changed to two (2) to represent the subcategories under the training dataset. According to [5]-[11], this last layer is trained using by back propagation algorithm. The cross entropy cost function is then used to adjust the weight parameter by calculating the error between the output of the softmax layer and the label vector of the given sample category [5]-[11]. This last hidden layer has enough summarized information to provide the next layer which does the actual classification task.

V. RESULTS

The retrained model achieved a train accuracy of 45 – 60 %, cross entropy of 70 – 80% and validation accuracy of 34 – 50% as shown in fig. 2, 3 and 4 respectively.

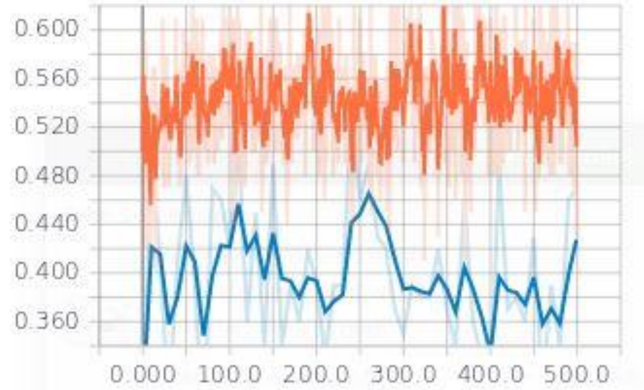

Fig. 2. Train accuracy

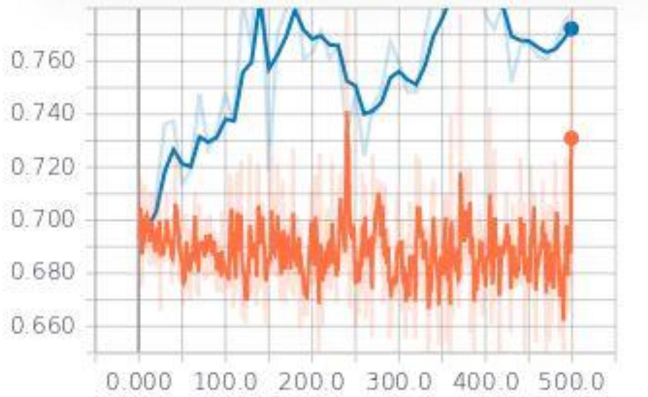

Fig. 3. Cross Entropy

The results for the test images were as shown in the Fig. 4 below.

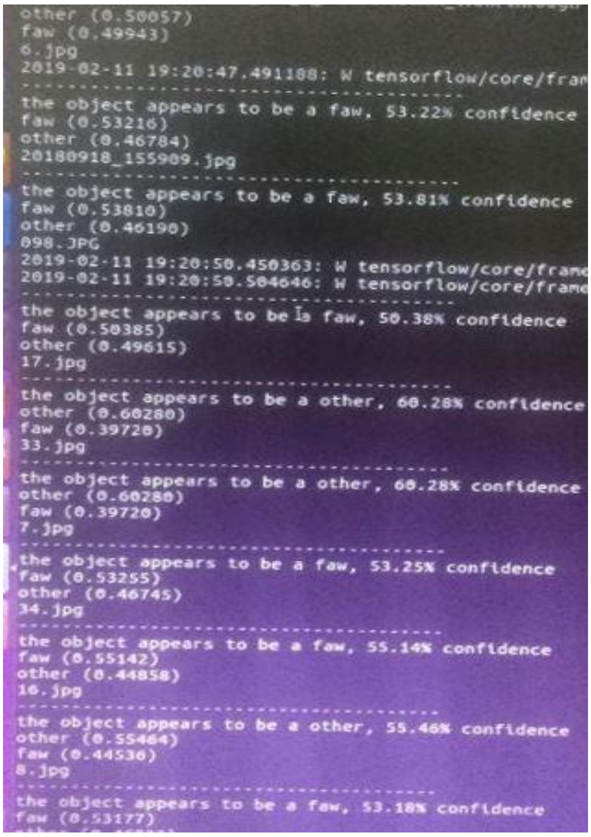

Fig. 4. Results for the test images.

VI. Conclusion

In this paper, we used Inception V3 in Google TensorFlow to identify FAW moth. We managed to achieve a train accuracy of 45 – 60 %, cross entropy of 70 – 80% and validation accuracy of 34 – 50%. The Inception V3 in Google TensorFlow is a power house for a pre-trained neural network [15], [16] and quicker experiment platform for researchers. As for future works, we want to explore the Google TensorFlow further and use it on single board computers such as the raspberry Pi.

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