Robotic Inference

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Abstract—Two neural networks are built on supplied data from Udacity and collected data from google images for image classification. Networks are trained and tested using the NVIDIA DIGITS work space. A Convolutional Neural Network is trained on the supplied data set to classify bottles, candy, or nothing at all using GoogleNet. A second Convolutional Neural Network is trained to identify certain pollination plants needed to help the bee population prosper using Alexnet.

Index Terms—Robot, IEEEtran, Udacity, LaTeX, deep learning.

1 Introduction

The lack of pollination corridors is threatening the existence of bees. Bees provide an important pollination service for most terrestrial ecosystems worldwide. In the United States, honeybees and thousands of species of native bees are responsible for pollinating crops, as well as garden, meadow, and forest plants. [1]

Plant identification can be time consuming, take many hours to complete by a human, and is inefficient. Here we look at developing an image classification network for identifying different pollinators quickly and accurately in an effort to help establish natural areas for potential pollination corridors for bees to thrive.

The network would be deployed on some type of uav that could collect images in various areas to identify what pollination plants exist naturally which would help understand how to make the environment more suitable for bee pollinators. This study is fairly basic and meant to set up a larger more in depth study on the topic with more time permitted. The plants chosen had similar characteristics as well as differing features to help with scoring. [2]

A preliminary study was done with a supplied data set to get comfortable with NVIDIA DIGITS platform. The study looked at an identification platform that would be used for a pick and place scenario.

2 Background / Formulation

NVIDIA DIGITS workspace provide three types of deep neural network LeNet, AlexNet, and GoogleNet as standard models for image classification, object detection, and semantic segmentation. In this study the two networks are built for image classification.

2.1 Supplied Dataset

For the first study with the provided image data set the accuracy of GoogleNet was the best model to run the provided dataset images through. It was best in terms of its accuracy and performance speed. 9 epochs were used, Stochastic Gradient Descent was chosen for the optimizer, and 0.001 for the learning rate.

2.2 Collected Dataset

AlexNet is chosen as the network for the data collected for my personal pollination classifier. It was chosen for it's accuracy as an image classifier, the ability it had to handle a larger pixel count, color, and wanting to test different platforms with DIGITS without using all my gpu time. 9 epochs were used, Stochastic Gradient Descent was chosen for the optimizer, and 0.01 for the learning rate.

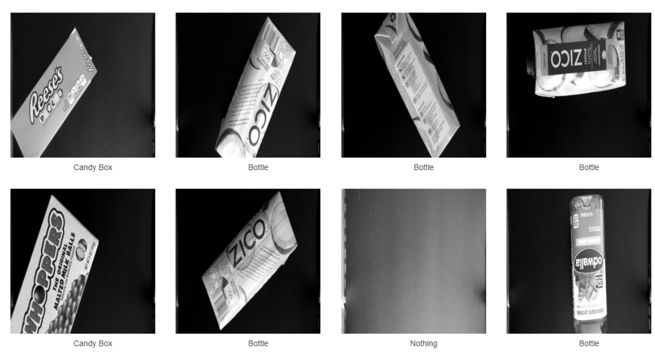

Fig. 1. Samples of supplied data from from udacity.

3 Data Acquisition

3.1 Supplied Dataset

The supplied dataset consists of photos taken from a Jetson TX-2 mounted over a conveyor belt provided by Udacity. There are (10,094) photos provided to identify bottles, candy box, or nothing. See Fig. 1 for example images and image breakdown.

TABLE 1
Supplied Dataset

bottle	4568 images
candy box	2495 images
nothing	3031 images

Each photo is a 8-bit RGB PNG image with the size of 500x500. The dataset is provided inside the workspace by Udacity.

Fig. 2. Samples of collected data from the google images that were resized and named.

3.2 Collected Dataset

The collected dataset consists of photos extracted from a google image search from a google image download plugin. Due to the nature of the pollination problem images were hard to capture and instead images were extracted from google images with the idea in mind that if a robot came in contact with one of the flowers in the network it could identify it. A total of 990 images were collected to identify whether the flower was a latana flower orange, a geranium, or a typical sunflower. See Fig. 2 for example images and image breakdown.

Each photo is a 24-bit RGB PNG image with the size of 500x500. A script was generated to rename and resize the images using opencv and python. The dataset was uploaded to the Udacity workspace and then able to be accessed by

TABLE 2
Collected DataSet

latana flower orange	436 images
geranium	353 images
sunflower	201 images

DIGITS. The collected dataset is used only as a training set. Test set is then uploaded individually by images to get some results on how well the plants are identified.

4 Results

4.1 Supplied Dataset

An 'evaluation' command provided by Udacity was used for testing the network. The maximum inference time was 4.8ms and the accuracy was 75.4 percent, which meet the numerical requirements of 10ms and 75 percent.

4.2 Collected Dataset

The accuracy of the network on the training set was around 92-96 percent. The network was tested on the NVIDIA DIGITS. Nine images were tested by the network to see how accurate the model performed.

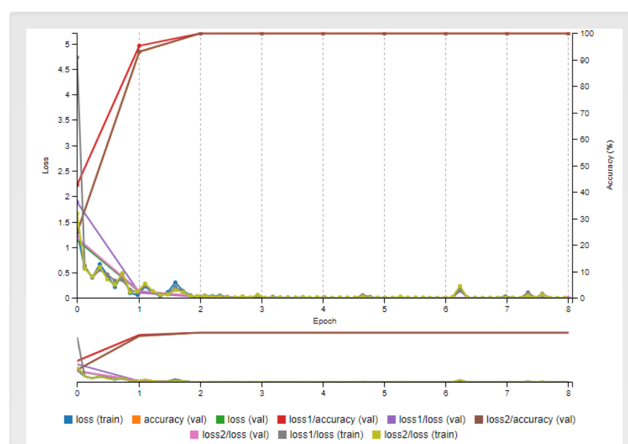

Fig. 3. Performace of the supplied dataset.

5 Discussion

5.1 Supplied Dataset

The supplied dataset performed quite well with the Googlenet model and the amount of epochs that were used. Adjusting the learning rate to 0.001 really helped the performance. It wasn't necessary to go over nine epochs to get the results needed to pass the evaluation step, however, tuning up the learning rate really helped the evaluation performance numbers.

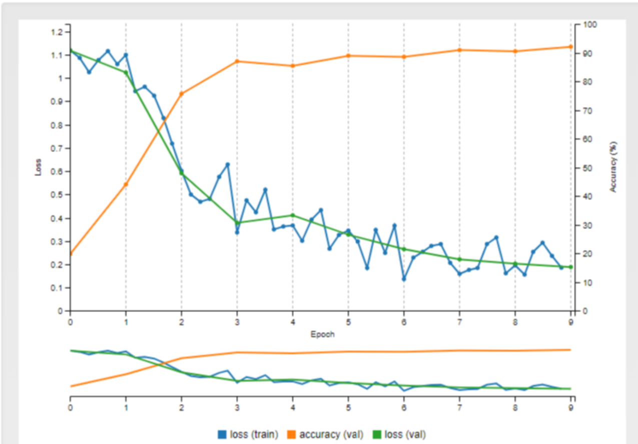

Fig. 4. Performance of the collected dataset.

5.2 Collected Dataset

The network performs well on the test set. An accuracy of more than 90 percent suggest that the network would perform well in the field, however at this point, their is no way to prove how the network would perform as an inference model simply because the data was collected from google images and not an rgb camera.

To speed things up and still get great accuracy the Alexnet model was used for this study. The model only needed a 0.01 learning rate to achieve the proper results. With some time and effort put into this it would be feasible to generate a new data set from a rgb camera for an inference model. It is good to note the accuracy may drop if the network performs classification on images in the field with this network, but, the idea is there! The evaluate command did not work for this model.

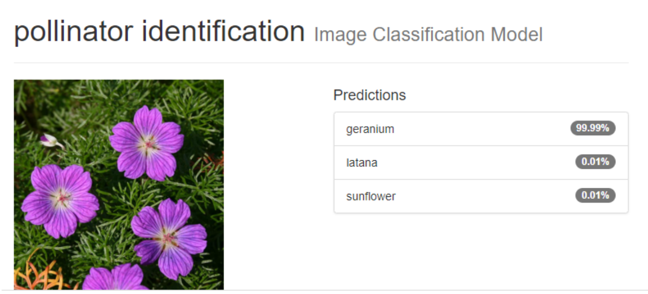

Fig. 5. Geranium tested and achieved a score of 99.9 percent accuracy.

6 Conclusion / Future work

This project was meant to open a conversation to further investigate how machine learning could be implemented in a agricultural sector related to bee pollinators. Further studies of this subject would require object detection and semantic segmentation as platforms for gathering more accurate results. All in all, the project opened a conversation that is critical and important to future of pollination while achieving high accuracy with a convolutional neural network.

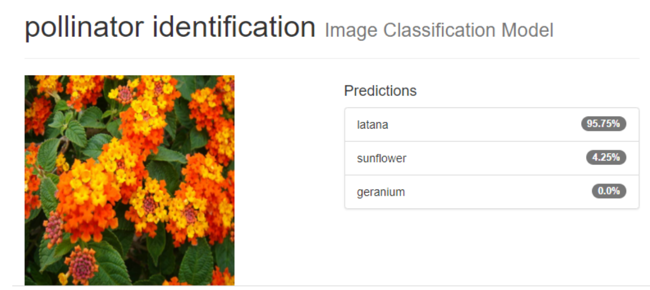

Fig. 6. Latana Flower Orange tested and achieved a score of 95.9 percent accuracy.

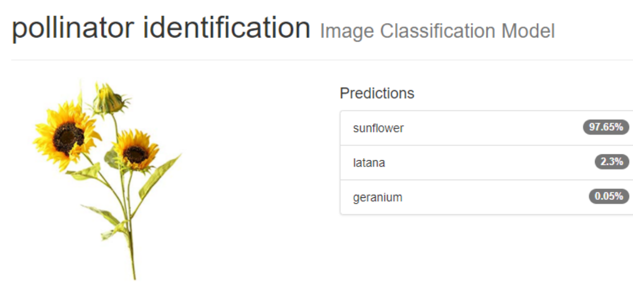

Fig. 7. Sunflower tested and achieved a score of 97.65 percent accuracy.

In conclusion, convolutional neural networks achieve results that could be helpful for early studies in the field pollinator identification. Field researchers, land managers, educators, civil servants, and the interested public would greatly benefit from accessible, up-to-date tools automating the process of species identification. [3]

References

[1] W. M. Institute, *Native Pollinators: Fish and Wildlife Habitat Management Leaflet*. https://www.mofga.org/Publications/The-Maine-Organic-Farmer-Gardener/Winter-2014-2015/Plant-Corridors, 2005.

[2] J. Wäldchen, M. Rzanny, and P. Mader, *Automated plant species identification—Trends and future directions*. https://journals.plos.org/ploscompbiol /article?id=10.1371/journal.pcbi.1005993s, 2018.

[3] J. Wäldchen, M. Rzanny, and P. Mader, *Automated plant species identification—Trends and future directions*. https://journals.plos.org/ploscompbiol/article?id=10.1371 /journal.pcbi.1005993s, 2018.