A Transfer Learning Approach to Pollinator Recognition

Final Project Report

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Abstract

In this final report, we will present the recent progress of our project after 11 weeks of work. We implemented a transfer learning approach by using a pre-trained convolutional neural network, called AlexNet, to classify and recognise images from six insect pollinator groups—bees, beetles, butterflies, flies, moths and wasps. We fine-tuned layers from the AlexNet convolutional neural network to learn the specific features of our dataset. The main aim was to train our pollinator recognition model on the basis of all six classes, but we also trained and tested the model on the basis of the number of classes, which was two, three and five. With two classes, beetles and butterflies, the accuracy reached 95%. With three classes, bees, beetles and butterflies, the accuracy achieved 87%. With five classes, bees, beetles, butterflies, wasps and moths, the accuracy achieved __%. Finally, with all six classes, the model did not perform at its best, and the accuracy decreased to 70%.

A Transfer Learning Approach to Pollinator Recognition

In recent years, new methodologies for image processing have used convolutional neural networks (CNNs). CNNs are the most commonly used type of deep learning; they contain several layers of convolutional, non-linear, pooling and fully connected layers that process and transform input data to produce the output (Deshpande, 2016). When the CNN model is trained from scratch, it is called deep learning. When knowledge of one type of problem, gained through deep learning, is used to solve a similar problem, it is called transfer learning (Patel & Pingel, n.d.).

Akçay et al. (2016) proposed a method to classify baggage according to type by using transfer learning within X-ray baggage security imagery. They addressed the following two specific target problems: a two-class firearm detection problem and a multiple-class object classification problem; the classes were firearms, firearm components, knives, ceramic knives, cameras and laptops. They fine-tuned the layers of AlexNet CNN by starting with the fourth one to the eighth layer and by freezing the first three layers. The accuracy achieved 98% for classical handgun detection. Kandaswamy, Silva and Alexandr (2016) used single-cell deep transfer learning for high-content analysis of breast cancer to stimulate the development of new drugs that are effective against a wide spectrum of cancer. In their work, they combined deep learning and transfer learning. The use of transfer learning attained a 2% accuracy improvement compared with the use of the deep learning approach and was 30% faster, as well.

In this project, we implemented and developed our pollinator recognition (PR) model by using the transfer learning method to classify the following six different insect pollinators: bees, beetles, butterflies, flies, moths and wasps. We use this technique to train our PR model because transfer learning models do not require a significant number of data nor a long time to train.

Materials and Methods

Dataset

The number of collected images was as follows: 1475 images for the bee class, 745 for the beetle class, 731 for the butterfly class, 1002 for the fly class, 412 for the moth class and 653 for the wasp class. We created modified versions of the existing images for the classes of beetles, butterflies, moths and wasps to increase the amount of image data within these classes. The image dataset contains an unequal number of images per category, so we adjusted the dataset to make the number of images balanced on the basis of the lowest number. To enable us to use most of the collected data, we performed the modified versions' images. Then, the entire dataset was divided into two datasets, in which 80% of the images were used for training, and the rest were used for testing.

Framework

The algorithm for this model was developed on the basis of a pre-trained CNN called AlexNet. The layers were transferred to the new task, except for the last three layers, which consisted of a fully connected layer, a softmax layer and a classification output layer. Notably, this project used the 23-layer version of AlexNet rather than the 25-layer one. The difference between these two versions is that the newer one consists of two dropout layers to manage overfitting whilst training the data (Mathworks, n.d.). We borrowed this step and added one dropout layer before the fully connected layer. We also modified the input layer to include a parameter for data augmentation. A pre-processing function was applied to the image dataset before the algorithm was run. A further modification was applied whilst running the PR model, and this was based on two classes, those of the bees and the flies. Two dropout layers were added, and one extra fully connected layer and a rectified linear unit (ReLU) in between these dropout layers were also added. Finally, the three outermost layers responsible for the classification task. The reason for adding these extra layers was that the first version of the PR model did not work optimally for these two classes, so we conducted the experiments to improve classification accuracy.

Results and Discussion

We developed a deep transfer learning classification framework to recognise pollinators, and in doing so, we demonstrated that by fine-tuning existing CNNs, we can build on the knowledge acquired in solving one classification problem and apply it on another one. We fine-tuned two versions of the PR model, one with 24 layers and one dropout layer and the other with 27 layers and two dropout layers, one fully connected layer and the ReLU; in both versions, we modified the input layer. In general, we observed that the algorithm more accurately classified beetles and butterflies than it classified bees and flies.

Running the first version of the PR model on the basis of the problem of two classes, bees and flies, resulted in a 70% accuracy, approximately. With the latest modification, the accuracy improved and reached 80%. On the other hand, the PR model in its first version without the extra layers performed better for the classes of beetles and butterflies, with an accuracy of 95%. However, testing the PR model on the basis of all six classes in both versions did not result in a higher accuracy. We performed an additional step and segmented some of the image data within a certain category. The accuracy had a small improvement at 80% after the first version of the PR model with one dropout layer was ran.

Figure 1. Samples of the segmented bees.

Figure 2. Samples of the segmented flies.

In the confusion matrices in Figure 4, the numbers on the axes show the classes used: ‘1’ refers to bees, ‘2’ refers to beetles, ‘3’ refers to butterflies, ‘4’ refers to flies, ‘5’ refers to moths and ‘6’ refers to wasps. The accuracy was calculated as the sum of predicted labels compared with the tested labels, divided by the number of elements

$$\text{Accuracy} = TP + TN / TP + TN + FP + FN$$

After the algorithm was repeated multiple times, the accuracy fluctuated between 80% and 82% for all classes. All confusion matrices show the results of the first version of the PR model.

The ROC charts compare the classification models. The false positive rate (1–specificity) is illustrated on the X-axis against the true positive rate (sensitivity) on the Y-axis. The curve climbs towards the top left, indicating that the classes were correctly predicted by the model, and that any sensitivity increases are accompanied by a decrease in specificity. The closer the curve is to the Y-axis and the top of the border, the more accurate is the test.

The AUC was based on the traditional academic point system[1]. The model was between being a fair system and a good system.

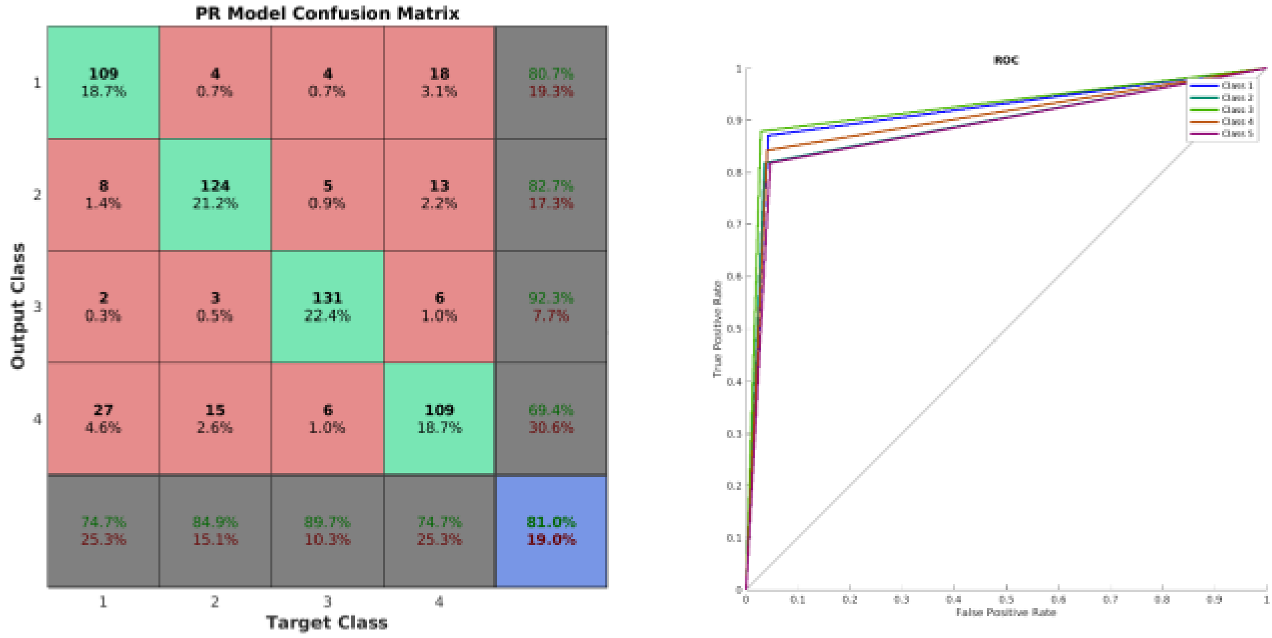

Figure 3. 1 refers to the class of bees; 2, the beetles; 3, the butterflies; and 4, the flies.

[1] The categories are as follows: 0.90–1, excellent (A); 0.80–0.89, good (B); 0.70–0.79, fair (C); 0.60–0.69, poor (D); and 0.50–0.59, fail (F).

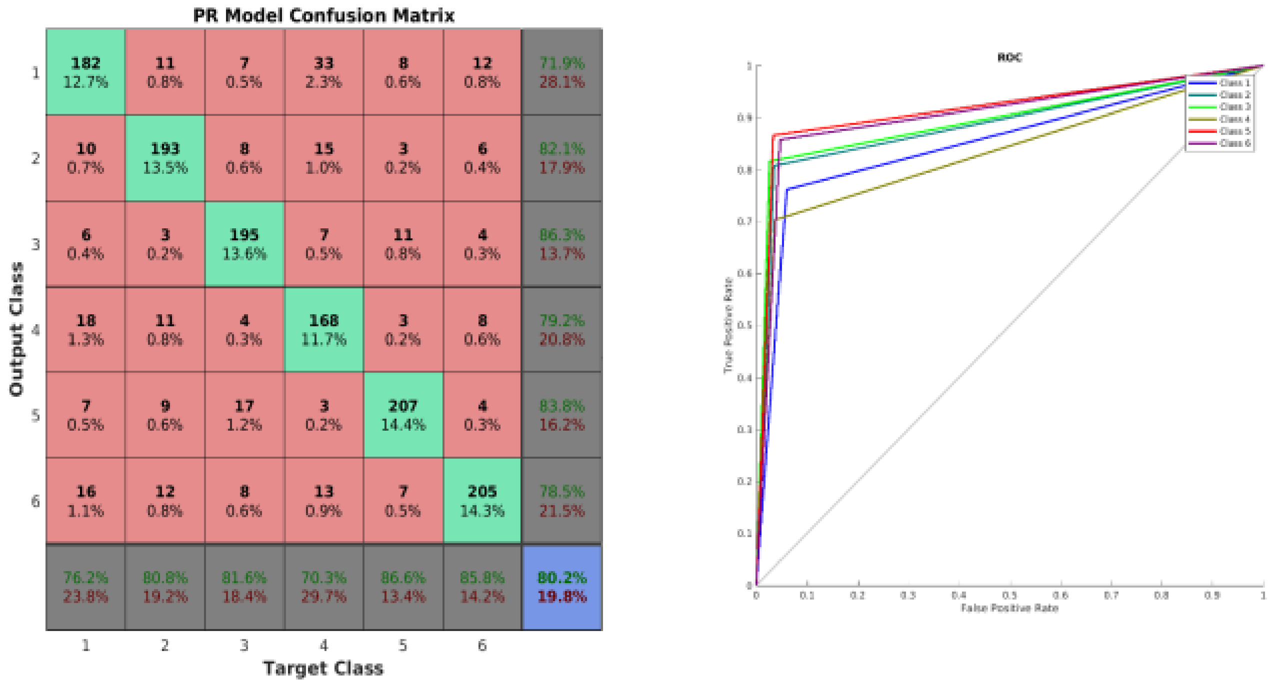

Figure 4. 1 refers to the class of bees; 2, the beetles; 3, the butterflies; 4, the flies; 5, the moths; and 6, the wasps.

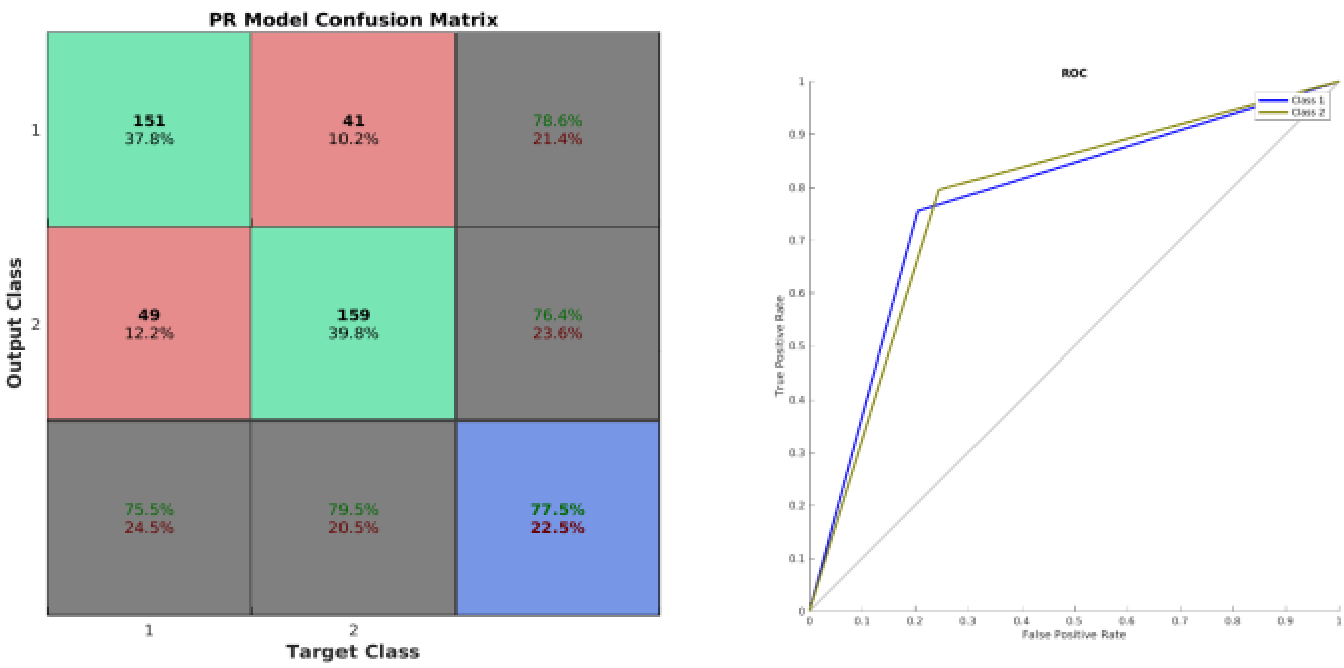

Figure 5. 1 refers to the class of bees; 2, the beetles; 3, the butterflies; and 4, the flies.

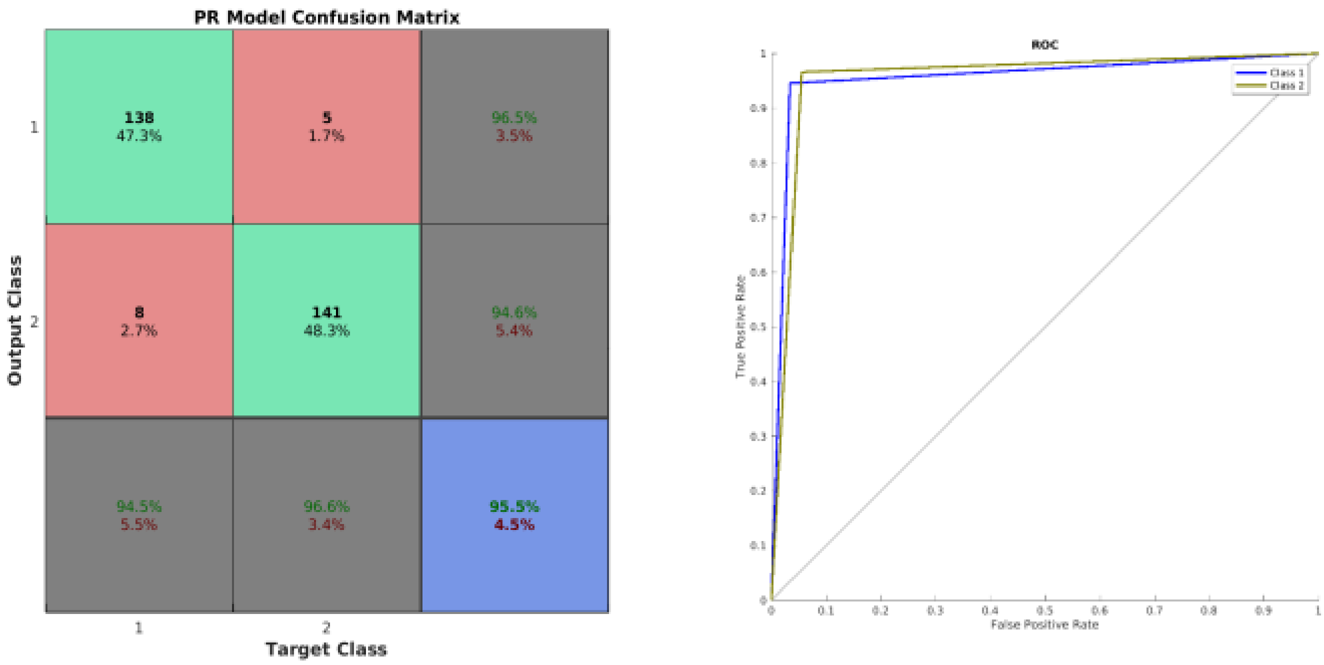

Figure 6. 1 refers to the class of beetles, and 2 refers to the class of butterflies.

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