USING DEEP LEARNING ALGORITHMS TO OPTIMIZE A NEW MARK-RECAPTURE TECHNIQUE FOR TREE-KILLING BARK BEETLES

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**ABSTRACT:** Whereas mark-recapture studies are sometimes used to estimate population size, mark-recapture studies initiated by Natural Resources Canada attempt to estimate movement of individuals in the population by marking them at source locations and recapturing them at various surrounding trap sites. A novel variation of traditional mark-recapture techniques developed by Natural Resources Canada involves coating trees with paper such that the beetles are marked with paper dust as they emerge. Recaptured beetles are then photographed under black light, which causes paper dust to fluoresce. In this work, we classify images of the recaptured beetles as marked or unmarked using deep neural networks. We use transfer learning where existing top-performing classifiers are applied to our beetle image classification problem. We compare the performance of two top performing deep learning models by varying certain parameters, and finally obtain the most optimal model to classify images.

**KEYWORDS:** image classification, machine learning, mountain pine beetle, forest insect, dispersal, population ecology, deep learning, mark-recapture, dispersal, mountain pine beetle

1. INTRODUCTION

Since 1990, an outbreak of the mountain pine beetle (*Dendroctonus ponderosae*) has affected over 20 million hectares of forest in western Canada, making it the among the largest recorded forest insect outbreaks in North American history(Kurz et al. 2008; S. W. Taylor and Carroll 2003). Mountain pine beetle adults disperse to attack and colonize trees to lay eggs beneath the outer bark(Safranyik and Carroll 2006). The process of attack and colonization results in tree death(Dhar, Parrott, and Hawkins 2016; Safranyik and Carroll 2006). Although understanding beetle dispersal in this context is vital in making well-informed environmental decisions(Robertson, Nelson, and Boots 2007), quantifying beetle dispersal is challenging because adult mountain pine beetles are too small to be tracked using attached radio-emitting devices at the time of this study.

Due to the difficulty associated with tracking the movement of mountain pine beetles, many studies that estimate their dispersal, do so based on the locations of trees they have killed without certain knowledge of the origin and destination of individual beetles (Robertson, Nelson, and Boots 2007; Goodsman et al. 2016; Powell and Bentz 2014). Instead of inferring where beetles start and end based on the locations of killed host trees, an alternate approach for quantifying dispersal uses of mark-recapture techniques wherein marked insects are released from a known release point and subsequently recaptured in traps set at varying distances from the release location (Turchin and Thoeny 1993; Safranyik et al. 1992; Reid and Reid 2008; Dobzhansky and Wright 1943). Dispersal kernels that describe the probability of dispersing to locations from a release point can then be constructed from these data (L. R. Taylor 1984).

Most mark recapture studies of the dispersal propensity of tree-killing bark beetles have marked beetles with brightly fluorescing powder either by coating the beetles directly (Safranyik et al. 1992) or by coating the outside of the tree so that as beetles emerge prior to dispersal, they self-mark (Turchin and Thoeny 1993; Linton et al. 1987). Studies have found, however, that coating beetles in fluorescing powder can result in decreased beetle longevity (Cook and Hain 1992)or in a reduction of beetle body condition, which could result in shorter flight duration of coated individuals relative to unmarked individuals (Reid and Reid 2008). If flight duration is reduced in insects marked with fluorescent powder, then models of dispersal based on mark-recapture studies that use fluorescent powder will underestimate insect dispersal capacity. An additional problem associated with some mark recapture studies is the method of mass release; unnaturally high densities of insects at the release site can result in atypical propulsive dispersal away from it. This can create unusual spatial dispersal relative to animals that are allowed to disperse more naturally due to density-dependent dispersal away from high density locations (Dobzhansky and Wright 1943). To mitigate these problem, new and more natural methods of marking insects are required.

The goal of this work is to develop a new technique of marking and identifying marked insects that emerge from trunks of trees. A recently developed NRCAN marking technique involves covering trees in paper that fluoresces under black light such that the beetles are coated in paper dust as they emerge, thereby allowing the marked beetles to naturally disperse without direct human intervention. Mountain pine beetles emerging from papered trees and control trees are later captured and individually photographed under black light, which allows beetles to be categorized as marked or unmarked. Manually classifying each image as marked or unmarked can be tedious and prone to error, hence we automate the process using machine learning. The identification of marked insects is optimized by fine-tuning pre-existing image classification algorithms.

1. METHODS

We carry out the marking and identification of marked beeltes in two phases. The first phase involves setting up an outdoor experiment to mark the beetles. The trees from which the mountain pine beetles emerge are covered in paper that fluoresces under blacklight. In order to emerge from the trees, the beetles chew through the paper, getting marked in the process. Some of these beetles are later recaptured and photographed individually under a blacklight. This generates a data set consisting of images of beetles. This is explained in Section 2.1. The second phase involves using machine learning algorithms to classify the beetles. There are a variety of machine learning algorithms available for image classification (Tan and Le 2019; Szegedy et al. 2016; Simonyan and Zisserman 2015; He et al. 2016). We apply some top performing algorithms to our setting and run optimizations to obtain the best model with tuned parameters for our dataset. This is covered in Section 2.2.

* 1. EXPERIMENTAL DESIGN for marking  
     placeholder

EXPERIMENTAL DESIGN FOR IDENTIFICATION  
In this paper, we use Convolutional Neural Networks (CNNs) (add citation) to solve our image classification problem. However, to train on a very large dataset, deep CNN models may take a significant amount of time. A way to bypass this process is to re-use the model parameters from pre-trained top performing CNN models that were developed for standard computer vision benchmark datasets, such as the ImageNet image recognition tasks. This is the so-called transfer learning (add citation). We chose algorithms based on ResNet50 and EfficientNet as they are some of the top performing image classification techniques available (Tan and Le 2019; He et al. 2016). The optimization is done in two parts. In part I, we compare ResNet50 and EfficientNet by training those models on our original dataset and the “threshcropped” dataset (we explain how we obtain this new dataset in Section 2.2.2). The comparisons are made on the basis on score and time taken for the model to train. The basic definitions of these metrics can be found in (add citations here). In part II, we finetune the model with the highest score from phase I by varying certain parameters in our algorithm. After phase II, we obtain our “best model”. These techniques are discussed in further detail in Section 2.2.3.   
  
2.2.1 DATASET EXPLORATION   
Our dataset consisted of 1057 images primarily of mountain pine beetles (some other insects were also captured due to natural emergence from sections of tree infested by mountain pine beetles; they were photographed and recorded nonetheless) in .tif file format. Here is a sample of the filenames:

PaperedTransparent22v.tif

PaperedMixed24d.tif

PaperedControl4d.tif

NoPaperedGreen76v.tif

PinkPapierMache1d.tif

PinkPaintedPaper1v\_light.tif

Trap89072019540pmv.tif

The filenames of each image classified them as follows.

1. The first component of each name provides information on the source from where the beetles were captured.
2. “Papered” and “NoPapered” determines whether the tree segment from where the beetle in the image emerged was papered or not. Mountain pine beetles that emerged from papered bolts were considered marked whereas those that emerged from unpapered bolts can be considered unmarked. For example, PaperedMixed24d.tif is considered marked and NoPaperedGreen76v.tif is considered unmarked.
3. “Trap” indicates that the beetles originated from a separate outdoor experiment in which standing trees that were infested with mountain pine beetles were papered. A number of Lindgren funnel traps were set up in the vicinity to capture beetles emerging from trees in the area. Most of the trapped beetles likely emerged from unmarked trees. For these beetles (and other insects), we do not know whether they emerged from papered trees. For example, Trap89072019540pmv.tif is the filename of a beetle in this category.
4. “PinkPapierMache” or “PinkPaintedPaper” also refer to marked beetles from papered trees.
5. The next component of each name is the color of the paint that was applied to the outside of the trees from which beetles emerged: Possible values of the paint color include: transparent, green, pink, mixed, or control (no paint). For example, PaperedControl4d.tif comes from a tree with no paint, whereas NoPaperedGreen76v.tif comes from a tree with green paint. If this component says “mixed”, this means that the beetles were mixed in a jar together to test the persistence of the marking paper in a slightly more realistic context. We note that mixing could potentially lead to cross-contamination of unpapered beetles because of physical contact with marked beetles or with paper fragments that may have been shed from them.
6. The third component is a number that is not unique to each beetle.
7. The final component indicates whether beetles were photographed on their dorsal (d) or ventral (v) sides. For example, PaperedControl4d.tif was photographed on its dorsal side. We note that the tips of the abdomens and the mandibles on the ventral side are a location of higher concentrations of paper particles in some cases when beetles were marked.
8. Another identifier that is added to some of the images is the label “light”. These images were not imaged under blacklight and had a very distinct look to them (see Figure 1) in comparison to the rest of the images.

A picture containing screen

Description automatically generated

Figure 1: Part (a) shows a sample image from the original dataset that is included in the training set. Part (b) shows an image with 'light' in the filename which is excluded due to its distinct appearance



2.2.2 REFINING THE DATASET  
To refine the input dataset to train the binary classifier, we only consider images with filenames that start with “Papered” or “NoPapered”. Papered filenames are considered marked beetles and NoPapered filenames are considered unmarked. We explicitly exclude filenames with “light” in them as their appearance was very different and we expect any new data given to our trained model for classification to be images of beetles photographed under a blacklight.

We do not include filenames with “Trap”. Most of these beetles likely emerged from unmarked trees. After obtaining the “best” model, we use it on this “Trap” dataset to classify them as marked or unmarked. We do not include filenames starting with the “Pink” tag, as they are from papered trees and hence marked. Including them would give us a dataset of 735 marked images and 278 unmarked images, which makes it quite unbalanced and may produce a heavy bias towards predicting marked beetles. \citation about unbalanced datasets in image classification? Upon removing these images, we were left with a total of 479 marked images and 278 unmarked images, which gave us a much better balance to begin training our machine learning algorithms on. We call this dataset of 757 images the original dataset.

We create a new of the original dataset to obtained images that are cropped and grayscale. We create this using thresholding to convert each image into one with a binary colour scheme and then cropping around the beetle. We therefore suggestively refer to this data set as the threshcropped dataset. See Figure 2 to compare a sample from each data set. This new dataset has a lower file size and excludes much of the coloured background from each image. Since we have streamlined the input and reduced file size, we wish to look at whether this will improve performance metrics.

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Figure 2: Original vs threshcropped beetles. The column label indicates whether the beetles are marked or unmarked. The first row consists of original images and the second consists of threshcropped versions of the same images.

2.2.3 OPTIMIZATION PROCESS   
We split each dataset into training and validation sets with an 80-20 ratio. We summarize how the data is split up in Figure 3.

We train Resnet50 and various EfficientNet models on both original and threshcropped datasets while keeping all variable parameters and preprocessing functions that go into the algorithm the same. More precisely, we train models written using *ResNet 50, EfficientNet B0, EfficientNet B3,* and *EfficientNet B7* on both the original and threshcropped datasets. We record the time taken, validation accuracy, and score based on the validation dataset. A member of our group classified the original images based on naked eye observations. We call this model the *human classifier* and calculate the accuracy and score of the human classification on the same validation dataset. This concludes part I of our tests to find the best way to classify these images.

In part II, to start, we pick the model with the highest score from part I. We vary two parameters – image size and batch size in the this algorithm for both original and threshcropped images. We include both kinds of dataset irrespective of which one did better in part I because we wish to see if we can get better or comparable metrics without needing to generate a threshcropped dataset. We obtain the accuracy and score calculated on the validation dataset for each iteration.

Chart

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Figure 3: The entire original dataset (757 images) is split into training dataset (605 images) and validation dataset (152 images). The figure shows the comparison of number of marked vs unmarked beetles in each dataset.

1. IMPLEMENTATION AND RESULTS  
   This section outlines the results obtained after carrying out the optimization procedure explained in Section 2.2.3.

In Part I, we train different models on our training dataset and collect the performance metrics in Table 1. We see that EfficientNet B7 and ResNet 50 perform better than the human classifier when we train them on the theshcropped dataset. We note that all models perform better with the threshcropped dataset. EfficientNet B0 runs the fastest but is outperformed by the rest in other metrics. EfficientNet B3 and B7 are costly in terms of time taken to run in most cases, so we eliminate them from phase II finetuning. ResNet50 takes longer than EfficientNet B0 but it produces much better accuracies and scores.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model | Original dataset | | | Threshcropped dataset | | |
| Time (min) | Accuracy (%) | score  (%) | Time (min) | Accuracy (%) | score (%) |
| Human Classifier | NA | 76.40 | 78.28 | NA | NA | NA |
| EfficientNet B0 | 50 | 63.15 | 77.41 | 41 | 75.65 | 82.94 |
| EfficientNet B3 | 398 | 63.81 | 77.73 | 74 | 79.60 | 84.42 |
| EfficientNet B7 | 628 | 67.10 | 77.06 | 909 | 76.31 | 82.17 |
| Resnet50 | 72 | 74.34 | 74.83 | 103 | 84.86 | 87.83 |

Table 1: Comparison of metrics of model performance

From this table, we conclude that Resnet50 with threshcropped images is the best model for further finetuning. Thus, we finetune Resnet50 in Part II. We include original images in our finetuning because we wish to see if we can get more improved metrics with the original dataset – this may eliminate the need to generate a threshcropped dataset. We only measure accuracy and score and drop the time comparison because the time taken by Resnet50 to train on the original and threshcropped datasets from Part I is comparable, moreover we now prioritize better prediction over time. We obtain the accuracy and score calculated on the validation dataset for each iteration. We summarize our results in Figure 4 and Figure 5.

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Figure 4: This figure summarizes the optimization workflow for the threshcropped dataset. Part (a) shows the best image size = 500, which is fixed at this value in part (b), which shows best batchsize of 30.

Line chart

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Figure 5: This figure summarizes the optimization workflow for the threshcropped dataset. Part (a) shows the best image size = 300, which is fixed at this value in part (b), which shows best batchsize of 32.

From Part II, we obtain the best parameters for Resnet50 for both the original and threshcropped datasets. We see in 6 that ResNet50 with original images yields very good metrics and outperforms its threshcropped counterpart, with an accuracy of 97.36% and an score of 97.93%. This is our best model. We use this best model classify the trap data (see section 3.1). In other words, we use ResNet50 with image size 300 and batch size 32 trained on original images. Out of 77 trap beetles, the classifier tells us that 64 are marked and 13 are unmarked. See Figure 7 to visualize the results.

1. Chart, bar chart

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Figure 6: Summary of metrics of the optimized models for original and threshcropped datasets

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Figure 7: Beetle images from the trap data along with the prediction probabilities

1. DISCUSSION  
   The marking and classification technique can be applied to any kind of insect that emerges from the barks of trees. The image classification technique can be applied to any system which needs binary classification of a collection of individual images. We initially do not see much improvement from the human classifier. However, after finetuning, we have dramatically better results, which shows that automating the process can improve the efficiency and the accuracy of the classification. Individually photographing beetles is still time consuming and labour intensive, so a potential refinement of this method involves photographing all the beetles at once and automating the process of picking out the number of marked beetles from one single image.

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SUPPORTING MATERIALS

[Table 1: Comparison of metrics of model performance 13](file:///C:\Users\mrays\Downloads\Marked%20beetle%20image%20analysis_DWG.docx#_Toc96539795)

[Figure 1: Part (a) shows a sample image from the original dataset that is included in the training set. Part (b) shows an image with 'light' in the filename which is excluded due to its distinct appearance 9](file:///C:\Users\mrays\Downloads\Marked%20beetle%20image%20analysis_DWG.docx#_Toc96539747)

[Figure 2: Original vs Threshcropped beetles. The column label indicates whether the beetles are marked or unmarked. The first row consists of original images and the second consists of threshcropped versions of the same images. 11](file:///C:\Users\mrays\Downloads\Marked%20beetle%20image%20analysis_DWG.docx#_Toc96539748)

[Figure 3: The entire original dataset (757 images) is split into training dataset (605 images) and validation dataset (152 images). The figure shows the comparison of number of marked vs unmarked beetles in each dataset. 12](file:///C:\Users\mrays\Downloads\Marked%20beetle%20image%20analysis%20(1).docx#_Toc96539749)

[Figure 4: This figure summarizes the optimization workflow for the threshcropped dataset. Part (a) shows the best image size = 500, which is fixed at this value in part (b), which shows best batchsize of 30. 14](file:///C:\Users\mrays\Downloads\Marked%20beetle%20image%20analysis_DWG.docx#_Toc96539750)

[Figure 5: This figure summarizes the optimization workflow for the threshcropped dataset. Part (a) shows the best image size = 300, which is fixed at this value in part (b), which shows best batchsize of 32. 14](file:///C:\Users\mrays\Downloads\Marked%20beetle%20image%20analysis_DWG.docx#_Toc96539751)

[Figure 6: Summary of metrics of the optimized models for original and threshcropped datasets. 15](file:///C:\Users\mrays\Downloads\Marked%20beetle%20image%20analysis_DWG.docx#_Toc96539752)

[Figure 7: Beetle images from the trap data along with the prediction probabilities. 15](file:///C:\Users\mrays\Downloads\Marked%20beetle%20image%20analysis_DWG.docx#_Toc96539753)

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