Binary Classification of Fire Ants and Native Ants in Japan

Junichi Takano

Project Background and Objectives

- Fire ants are native to South Africa and have now spread to more than 20 countries.
- Fire ants are highly aggressive, deliver painful stings, and can trigger allergic reactions, making them very dangerous.
- Japan, being an island nation, has seen fire ants enter the country by hiding in cargo on ships, with the first confirmed sighting in 2017.
- To prevent the spread of fire ants, the Japanese government inspects cargo and regularly surveys ports.
- When ants suspected of being fire ants are found, experts identify them.

By creating a model that can differentiate red imported fire ants from native Japanese ants based on images, I aim to speed up and enhance the efficiency of control measures for red imported fire ants.

Refining Target Species

- This is a binary classification task distinguishing fire ants from native ants, but in reality, there are about 300 native ant species in Japan.
- I narrowed down the types of native ants in Japan to focus on for this study.

Nationwide | Kanto region | Tokyo Port, Yokohama Port area

About 300 species | 117 species | 93 species

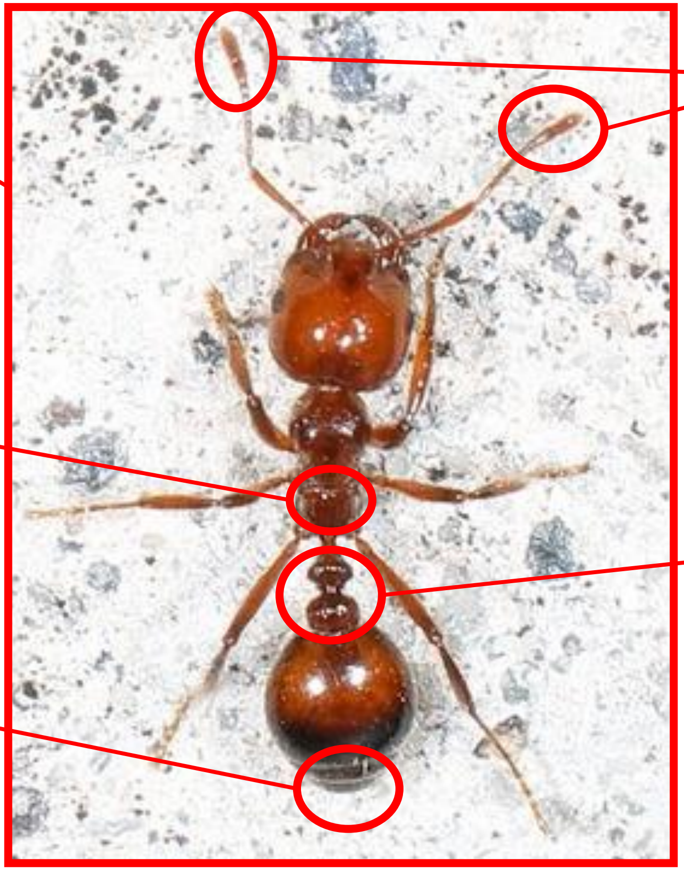
Data Source

iNaturalist

- An online platform where users can record and share their observations of plants, animals, fungi, and other organisms.
- Image identifications can be verified and reviewed by other users, and if at least two-thirds of identifiers agree on the results, the data is considered research-grade.
- In this study, I used only research-grade images.

Rarity	Target species	Image obtained	Over 100 images
Most Common	22	22	13
Common	30	30	9
Rare	35	25	4
Extremely Rare	6	3	3
Total	93	80	29

Characteristics of Fire Ants



➢ Images that clearly show the details of ants are needed.

Image Filtering Using OpenCV (cv2)

- OpenCV (Open Source Computer Vision Library)

  An open-source library for computer vision, image processing, and machine learning.

- cv2

  The Python module of OpenCV

- Resolution checking

  Check the values representing the width and height of the image in pixels. Low-resolution images (small images) lack detail, making it difficult for the model to learn features

- Brightness checking

  Check the average intensity of the pixel values. Exclude images that are too dark or too bright.

- Blur detection

  Exclude out-of-focus and blurred images using the Laplacian variance method.

Results: Image Filtering Using OpenCV (cv2)

Low resolution

Blurry images

Additional Image Filtering

I created a model that classifies images containing clearly identifiable ants and images that do not.

Developing a Model for Image Filtering

Good images

Bad images

EfficientNetB0:

A family of convolutional neural networks (CNNs) introduced by Google in 2019.
EfficientNet models are designed to be efficient while maintaining high accuracy.
The B0 version is the baseline model in this family.

- Performed transfer learning using the pre-trained "EfficientNetB0" model.
- Fine-tuned the EfficientNetB0 model using 500 images with clearly visible ants and 500 images without clearly visible ants.
- Created a model that achieved 99.5% accuracy on the test dataset.

Results: Additional Image Filtering

I adjusted the threshold of the sigmoid function, which is the activation function of the final layer.

Threshold = 0.2

Fire ants: 7,235 images
Native ants: 9,487 images

Threshold = 0.5

Fire ants: 5,990 images
Native ants: 8,834 images

Threshold = 0.8

Fire ants: 4,957 images
Native ants: 8,157 images

Low — Image quality — High

Large — Sample size — Small

➢ Using the class weights method, I trained the model to address the imbalance in the number of samples between classes.

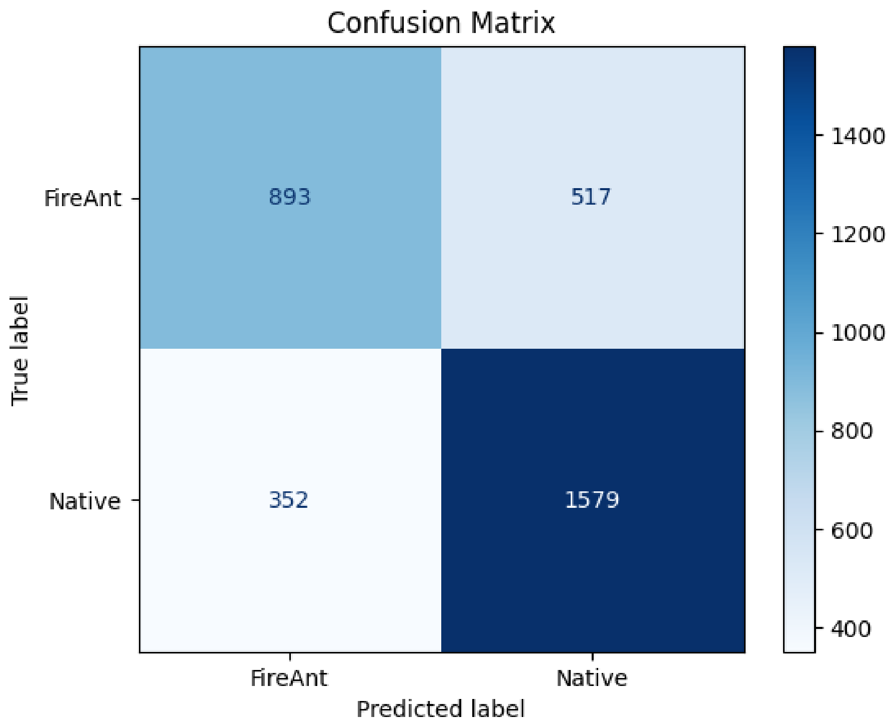
Models

Model	# Layers	Parameters (M)	Top-1 accuracy on ImageNet(%)	Key Feature
Custom CNN (3 layers)	3	11	-	-
Custom CNN (6 layers)	6	1.2	-	-
EfficientNetB0	237	5.3	~77	A solid general-purpose model, easy to train
EfficientNetB5	340	30	~83	Larger version of B0, better accuracy
ResNet50	50	25	~76	Classic, robust model
Xception	71	22	~79	A good mix of efficiency and accuracy

Results: Custom CNN (Threshold = 0.2)

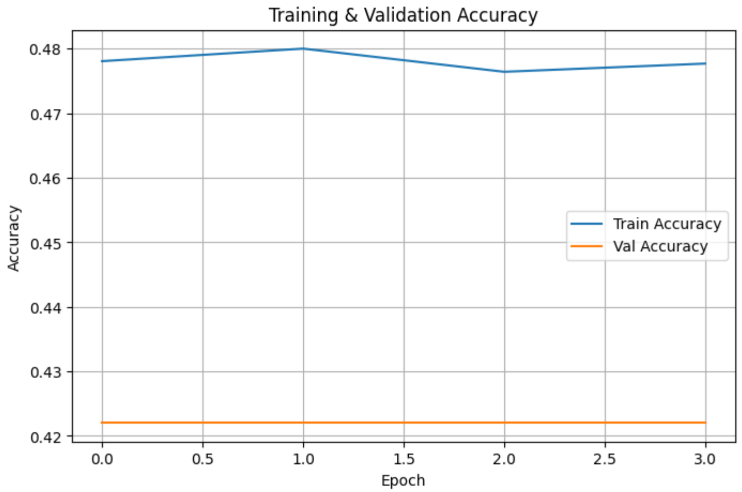
3-layer Custom CNN

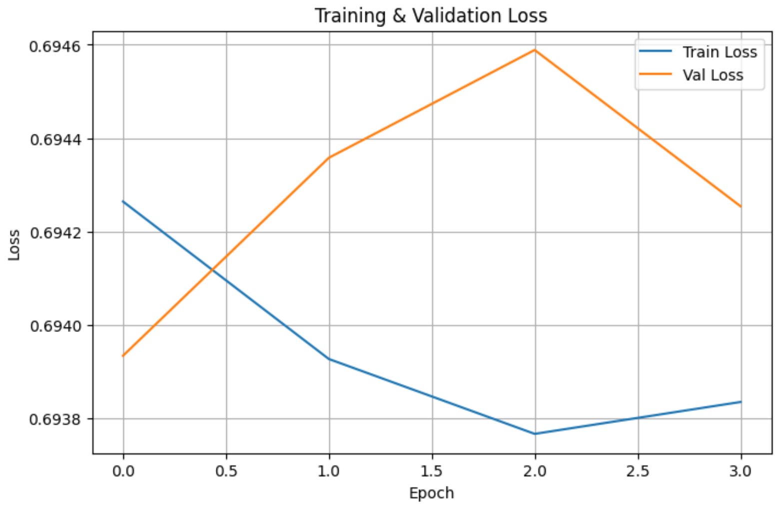
(Parameters adjusted using grid search)



Accuracy	0.7399
Precision	0.7533
Recall	0.8177
F1 Score	0.7842

6-layer Custom CNN



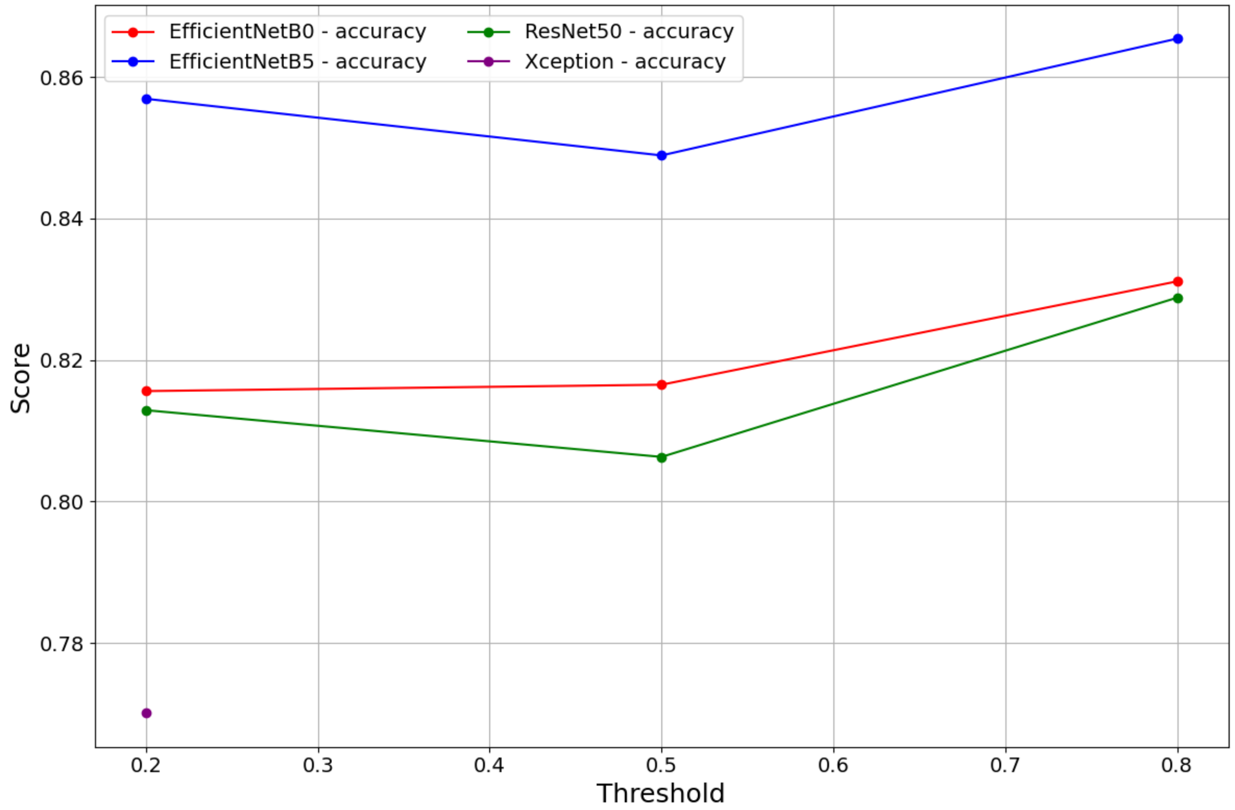


When the layers were deepened, there likely weren't enough samples for the model to learn the pattern from scratch.

Fire ants: 7,235 images
Native ants: 9,487 images

Results: Pre-trained Models

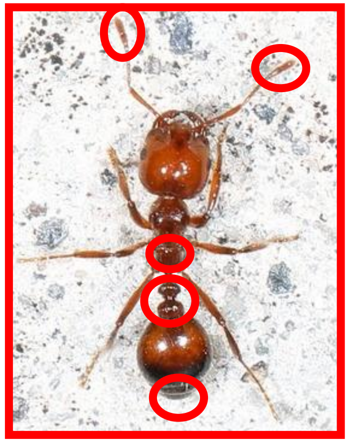
Model	Threshold = 0.2				Threshold = 0.5				Threshold = 0.8			
	Accuracy	Precision	Recall	F1 Score	Accuracy	Precision	Recall	F1 Score	Accuracy	Precision	Recall	F1 Score
EfficientNetB0	0.816	0.850	0.827	0.838	0.817	0.842	0.859	0.851	0.831	0.873	0.857	0.865
EfficientNetB5	0.857	0.871	0.883	0.877	0.849	0.867	0.889	0.877	0.865	0.891	0.898	0.894
ResNet50	0.813	0.823	0.861	0.842	0.806	0.842	0.839	0.841	0.829	0.875	0.851	0.863
Xception	0.770	0.781	0.836	0.808	-	-	-	-	-	-	-	-



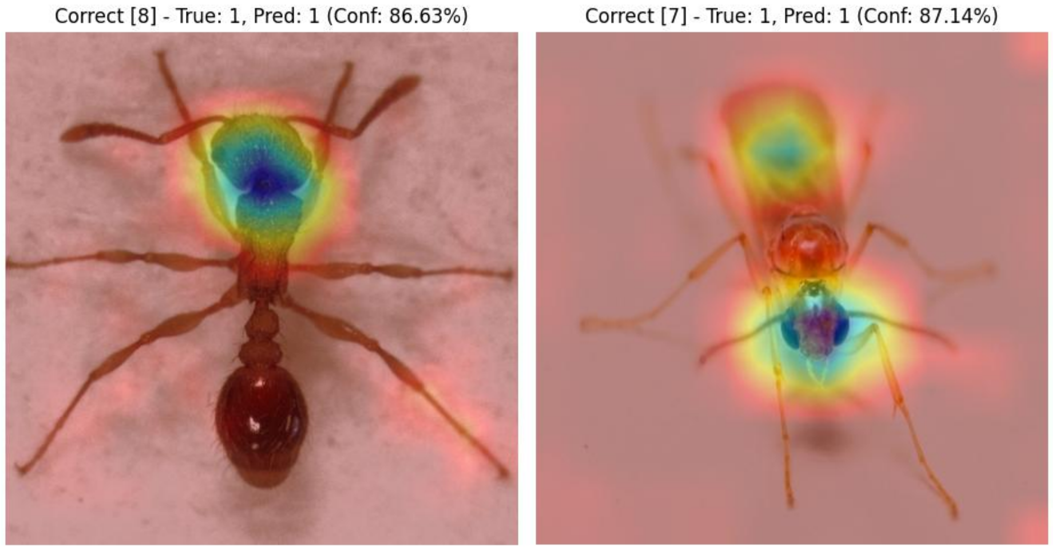
Class Activation Map (Grad-CAM): EfficientNetB5

- A Class Activation Map (CAM) is a technique to visualize which parts of an input image a Convolutional Neural Network (CNN) uses to make a classification decision.

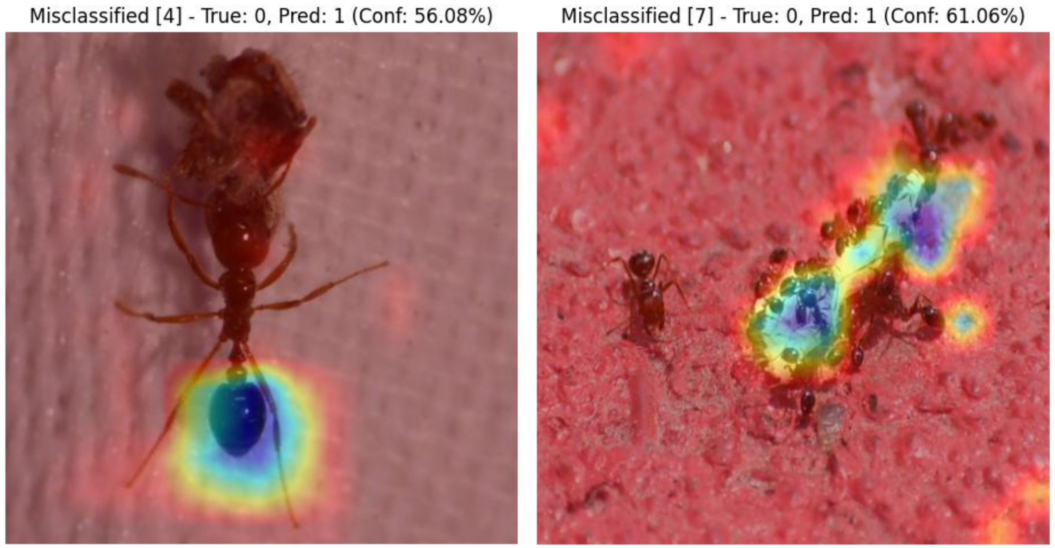
- Gradient-weighted Class Activation Mapping (Grad-CAM) is an extension of CAM that works for any CNN-based architecture



Correct



Misclassified



Evaluation of Generalization Performance

Availability of images of native ants

Rarity	Target species	Image obtained	Over 100 images	Less than 100 images
Most Common	22	22	13	9
Common	30	30	9	21
Rare	35	25	4	21
Extremely Rare	6	3	3	0
Total	93	80	29	51

Model building

Test generalization performance

Accuracy in test images

Model	Threshold = 0.2	Threshold = 0.5	Threshold = 0.8
EfficientNetB0	0.8480	0.8755	0.8710
EfficientNetB5	0.9904	0.9994	1.0000
ResNet50	0.8714	0.8291	0.8404
Total test images	1664	1615	1535

Summary

Results

- The model using EfficientNetB5 showed the highest accuracy, with an accuracy of approximately 86%.

- High-quality images are important for building accurate models.
  - Images with the entire ant in focus
  - Images showing one clearly visible ant instead of multiple ants
  - Images that avoid including anything other than ants as much as possible

- The models demonstrated good generalization performance.

Future work

- Obtaining images of native ants that were not available this time.

- Collecting various types of images, such as those showing multiple ants.

Questions?

Please speak slowly or in Japanese!