Advanced Classification of Beetle Doppelgängers Using Siamese Neural Networks and Imaging Techniques

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Abstract.

The precise identification of beetle species, especially those that have similar macrostructure and physical characteristics, is a challenging task in the field of entomology. The term "Beetle Doppelgängers" refers to species that exhibit almost indistinguishable macrostructural characteristics, which can complicate tasks in ecological studies, conservation efforts, and pest management. The core issue resides in their striking similarity, frequently confusing both experts and automated systems.
The study aims to overcome these constraints by presenting a sophisticated methodology that combines Siamese Neural Networks (SNNs) with advanced imaging techniques, thus enhancing the accuracy and efficiency of beetle species categorization. This research intends to exploit the unique computing capabilities of SNNs by utilizing their capacity to handle and compare detailed visual input. It employs advanced image processing methods to uncover and evaluate the complex aspects of beetle morphology. The effectiveness of this integrated technique is demonstrated by its significant improvement in feature extraction accuracy. SNNs can detect the subtle but important morphological distinctions that define Beetle Doppelgängers through comparative analysis. In this study, the methodology is applied to an image dataset that includes images of both the Red Flour Beetle and the Rusty Grain Beetle, two species known for their visual mimicry.
Remarkably, the SNNs achieved accuracy rates of over 95% in both the training and testing stages. These results show that the system has the capacity to precisely detect subtle morphological variations, a task that conventional classification algorithms have traditionally found difficult to accomplish. In addition, the SNN model consistently exhibited a high level of

precision when evaluated using new, unknown data. Despite a slight decline in performance throughout the testing phase, which is typical for most machine learning models, the SNN exhibited a strong ability to generalize from its training. The model's practical applications are emphasized by its capacity to significantly streamline species identification, boost the accuracy of ecological data, and optimize pest control strategies with an unparalleled level of precision. The study has revealed that SNNs are a revolutionary technique for identifying Beetle Doppelgängers, providing a significant advancement in entomological methodology. This study not only supports that SNNs may be used effectively to differentiate complicated species, but also establishes a standard for future research in automatically classifying physiologically similar objects.

Keywords. *Doppelganger beetle; Entomological informatics; Morphological similarities; Red flour beetle; Rusty grain beetle; Siamese neural networks.*

Introduction

Classifying beetle species is a crucial task in the field of entomology, with important consequences for biodiversity studies, ecosystem management, and agricultural practices. Beetles, which are classified under the order Coleoptera (Krinsky, 2019), are one of the most varied collections of organisms on earth. Nonetheless, the presence of "Beetle Doppelgängers" — species that are practically alike in their physical characteristics — poses a distinctive array of difficulties. Conventional techniques for identifying species, which mostly involve analyzing their physical characteristics, sometimes prove inadequate when dealing with closely related species (Ng'endo et al., 2013). The constraints of conventional taxonomy, such as the necessity for specialized expertise and the subjective nature of morphological interpretation, highlight the need for more precise and scalable alternatives. Due to the diverse world of Coleoptera, the challenge of precisely distinguishing species is made more difficult by the presence of these "Beetle Doppelgängers" which are often mistaken for one another. This occurrence is not merely a taxonomic peculiarity, but a substantial hindrance in ecological investigation, pest control, and conservation endeavors (Bookwalter et al., 2023). The red flour beetle (*Tribolium castaneum* Herbst) (Coleoptera: Tenebrionidae) and the rusty grain beetle (*Cryptolestes ferrugineus* Stephens) (Coleoptera: Laemophloeidae) (Jian, et al., 2006) are famous instances of doppelgängers, whose subtle physical resemblances pose unique challenges for accurate classification.

Morphological Similarities and Differences

1. Red Flour Beetle (Tribolium castaneum Herbst)

Color and Texture: This beetle is characterized by its lightly punctated elytra, which can emit quinones, turning affected grain products a reddish hue — a feature lending to its common name. The coloration not only serves as a camouflage within its environment but also as a potential mix-up factor with similar species (Campbell, et al., 2003)
Shape: Viewed from above, the beetle exhibits a rounded head with large eyes extending toward the maxillary fossa, contributing to its streamlined shape which facilitates rapid movement through grain and flour.

Physical Adaptations: The end of its antennae bows strongly and is abruptly clubbed, enhancing its sensory capabilities within confined environments like processed grain stores.

2. Rusty Grain Beetle (Cryptolestes ferrugineus Stephens):

Color and Texture: As a member of the flat bark beetle super family Curcujoidea, it has a distinctly flat, small body which allows it to navigate and thrive under the bark and within flat surfaces, including processed goods where it is commonly found as a secondary pest.
Shape: The flatness extends from its head, which is level with the thorax, to its elytra, adorned with long striations that enhance its disguise against woody textures.
Physical Adaptations: Its physical structure, including a V-shaped arrangement of antennae and visible mandibles from a top-side view, equips it effectively for rapid movement across flat surfaces and climbing less porous materials like glass and plastic (Bharathi et al., 2023).

Figure 1 shows the outline images of the red flour beetle and the rusty grain beetle. The occurrence of Beetle Doppelgängers such as *T. castaneum* and *C. ferrugineus* serves as a prime example of the difficulties and requirements within the advancing area of automated species identification in entomology. By utilizing innovative computing technologies, we can effectively tackle these challenges and improve the precision of species classification. This, in turn, has a substantial impact on ecological studies, pest control strategies, and conservation efforts. It ensures that interventions are properly directed and based on biological knowledge. Figure 2 provides an overlapping outline image of these two beetles: the green-colored outline represents the rusty grain beetle, while the rustic red/brown outline represents the red flour beetle. Here you can see how machine learning approaches may misclassify these two species due to their size, shape, and other doppelgänger characteristics.

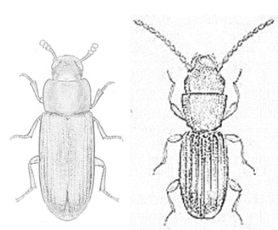


Figure 1. Outline images of the red flour (left) and the rusty grain beetle (right).

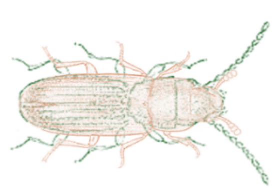


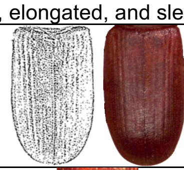
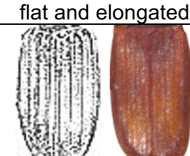
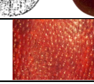
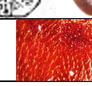
Figure 2. Overlapped image of the doppelganger beetle.

In further details, Figure 3 shows the split image of these two beetles, illustrating an intriguing comparison between the similar morphological characteristics. The right side of the image displays the red flour beetle, while the left side shows the rusty grain beetle. Despite the division, the overall continuity of the beetles' silhouette is maintained, suggesting that their general shape and size are quite similar. Both halves exhibit a pronounced pronotum and elongated elytra, which are characteristic of many beetles in the grain or bark beetle families. The texture appears finely punctated, especially on the elytra, providing a grainy appearance that would serve as effective camouflage within their natural habitats, like grain stores or bark.

The *antennae*, while not identical, maintain a segmented structure typical of beetles, which serves as a primary sensory organ. The legs on both sides of the image are positioned similarly, indicating a comparable stance and possibly similar mobility. This type of visual comparison is a powerful tool for highlighting both the differences and similarities that might not be apparent when the species are viewed independently.

Figure 3. Split image of the red flour (left) and rusty grain beetles (right).

Table 1. Some Commonalities of the red flour and rusty grain beetles.

Morphological similarities	Red Flour Beetle	Rusty Grain Beetle
Size	~2.3 mm to 4.4 mm	~1.6mm to 2.5mm
Color	dark reddish to brown coloration	reddish to brown coloration
Body shape	flat, elongated, and slender	flat and elongated
Elytra pattern		
Cuticle pattern		

Based on the figure above, some frequent physical traits contribute to their doppelgänger-like appearance and could be easily misinterpreted at first glance.

1. *Body Shape*: Both beetles have a compact, roughly cylindrical body that is typical for species that navigate through narrow spaces like grains.
2. *Coloration*: They share a similar brownish hue that helps them blend into their environment, making them less visible within the grains or flour they infest.
3. *Size*: Their small size is a shared characteristic that allows them to infest and hide within stored grain products effectively.
4. *Elytra*: Both have textured elytra that not only serve as protection but also aid in camouflaging them against predators and environmental factors.

The focus on these commonalities is on the broader morphological traits that would affect their identification at a macro level, especially in situations where detailed measurement of features like antennae length are not feasible as shown in Table 1.

Siamese Neural Network (SNN).

The emergence of digital imagery and machine learning has opened up new possibilities for improving species classification. Nevertheless, despite notable progress, the utilization of these technologies in entomological research has been predominantly restricted to basic implementations, frequently failing to tackle the intricacies associated with distinguishing closely related species. The advent of Siamese Neural Networks (SNNs) (Steiner, et al, 2023) and sophisticated image processing techniques offer a revolutionary chance to directly address these difficulties. These technologies have the ability to completely transform our understanding and categorization of beetle species by offering tools that are not only more precise but also significantly more efficient than the common neural networks. Moreover, unlike traditional neural networks that classify input data into predefined categories, SNNs are designed to assess and learn from the similarity between paired inputs. This feature is crucial when distinguishing between beetle species that appear almost identical to the untrained eye but may have significant biological and ecological differences.

Siamese Neural Networks have gained popularity in diverse domains that demand accurate and resilient feature differentiation, such as image identification, verification, and classification tasks (Malhotra 2023). Their unique architecture, which compares input pairs to learn discriminative features effectively, makes them particularly useful for tasks such as distinguishing between highly similar images or objects (LeCun et al., 2016). The implementation of image processing and machine learning technology has initiated a significant change in species classification by facilitating a more comprehensive and unbiased examination. Siamese Neural Networks (SNNs) are a promising technology among these options because they are effective at learning subtle distinctions between very similar images.

Methodology

Figure 4 illustrates the suggested conceptual framework. The technique is explained in the subsequent sections, providing a comprehensive explanation of each stage of the proposed project. Firstly, the input images are subjected to preprocessing in order to improve their quality. Subsequently, these images undergo a series of image processing methods including grayscale conversion, filtering, and edge detection. Feature extraction is the next step, where commonalities in patterns, colors, and other features are identified. Finally, the Siamese Neural Network (SNN) technique is used to automatically classify the two species of insects in this case. The model is trained, fine-tuned, and validated using a pre-trained model to assure accurate classification.

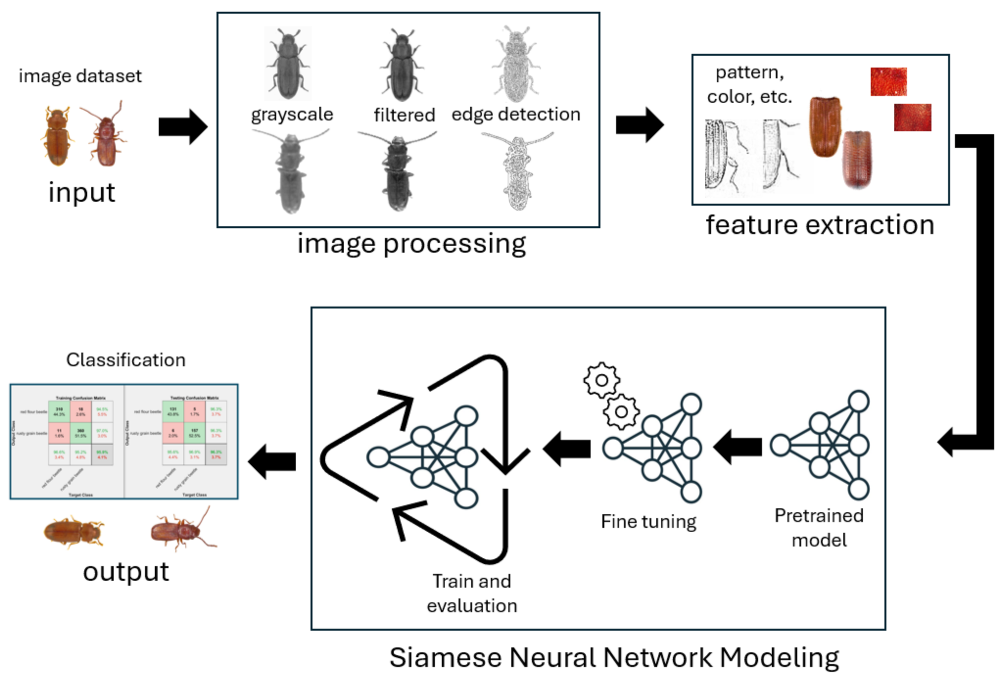


Figure 4. Block flow diagram of beetle doppelgängers discrimination.

1. Data Collection

Image Acquisition:

Sources: Collect high-quality images of the target beetle species (e.g., red flour beetle and rusty grain beetle) from the set-up test bed. Figure 5 illustrates the setup of the testbed, Figure 6 displays the physical features of the handheld mini magnifier camera, and Table 2 details its technical specifications.

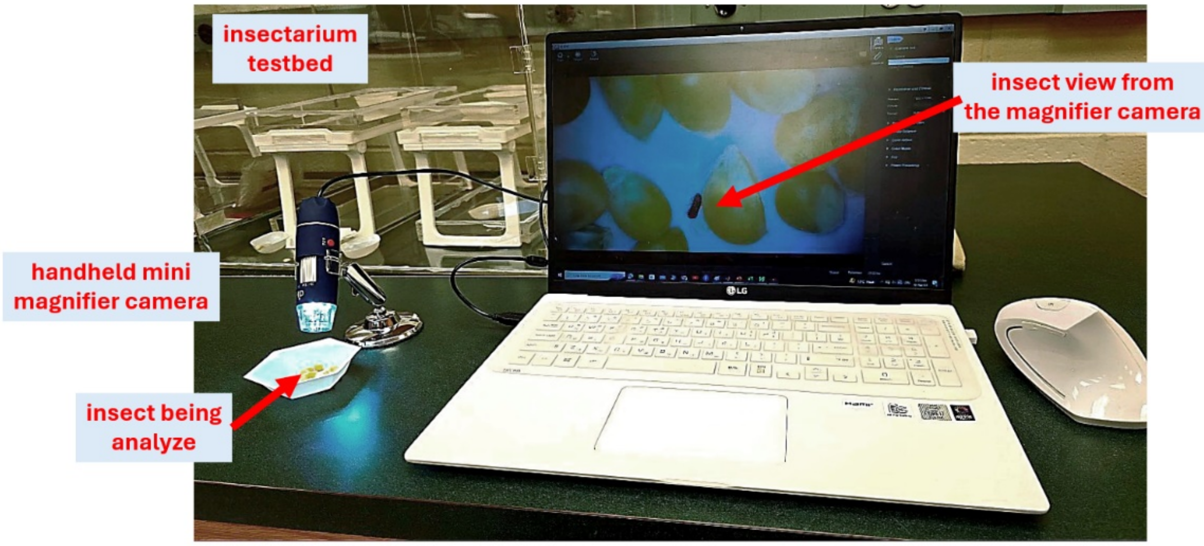


Figure 5. Testbed setup.

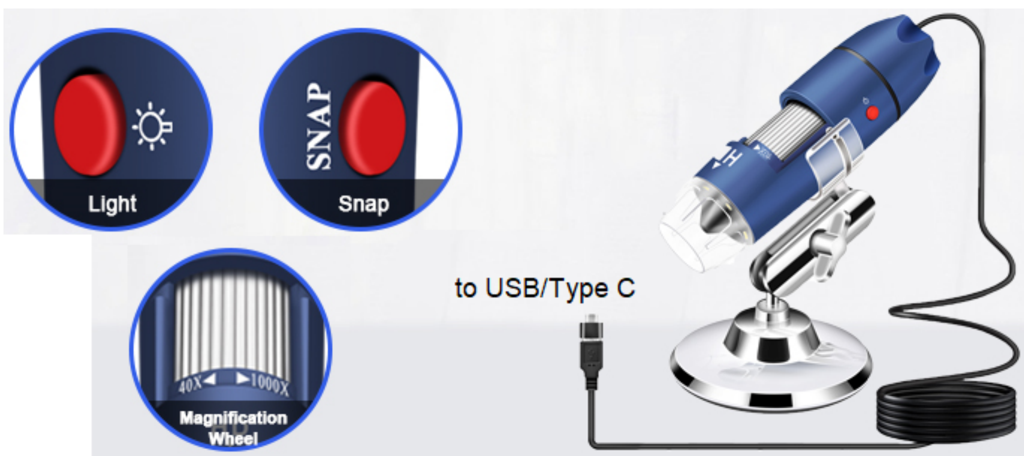


Figure 6. Handheld Mini Magnifier Camera.

Table 2. Magnification Endoscope Handheld Mini Magnifier Camera Specifications.

Brand/Company Name	Jiusion 2K HD 2560 × 1440P
Resolution	1280 × 720
Frame rate	Max 30 F/s
Focus range	1mm to ∞
Magnification	40X to 1000X
Video format	Mp4 or AVI
Photo format	JPEG or BMP
Light source	8 LEDs
Power source	5V DC
Compatible with	Android, Windows, Mac and Linux
Operating temperature	-4 °F to -140 °F

Image Annotation:

Labeling: Label images based on species identity. For SNN training, create pairs of images labeled as either ‘similar’ (same species) or ‘dissimilar’ (different species).

2. Data Preprocessing

The execution of image processing techniques and Siamese Neural Network (SNN) simulation was carried out quickly using customized MATLAB functions on the MATLAB 2024a platform. This platform offers a strong and effective environment, with complete analytical tools and innovative features, ensuring exact control and repeatability of our experimental methods. This configuration improved the dependability and accuracy of our findings.

Image Processing:

Standardization: Resize images to a uniform size (e.g., 224 × 224 pixels) to ensure consistency in input dimensions for neural network processing.

Augmentation: Apply data augmentation techniques such as rotation, scaling, cropping, and flipping to increase the robustness of the model against variations in beetle orientation and scale.

Feature Enhancement:

Filtering: Use image filters such as edge enhancement to highlight important morphological features like elytra patterns, antennae length/shape, and body contours.

3. Model Development

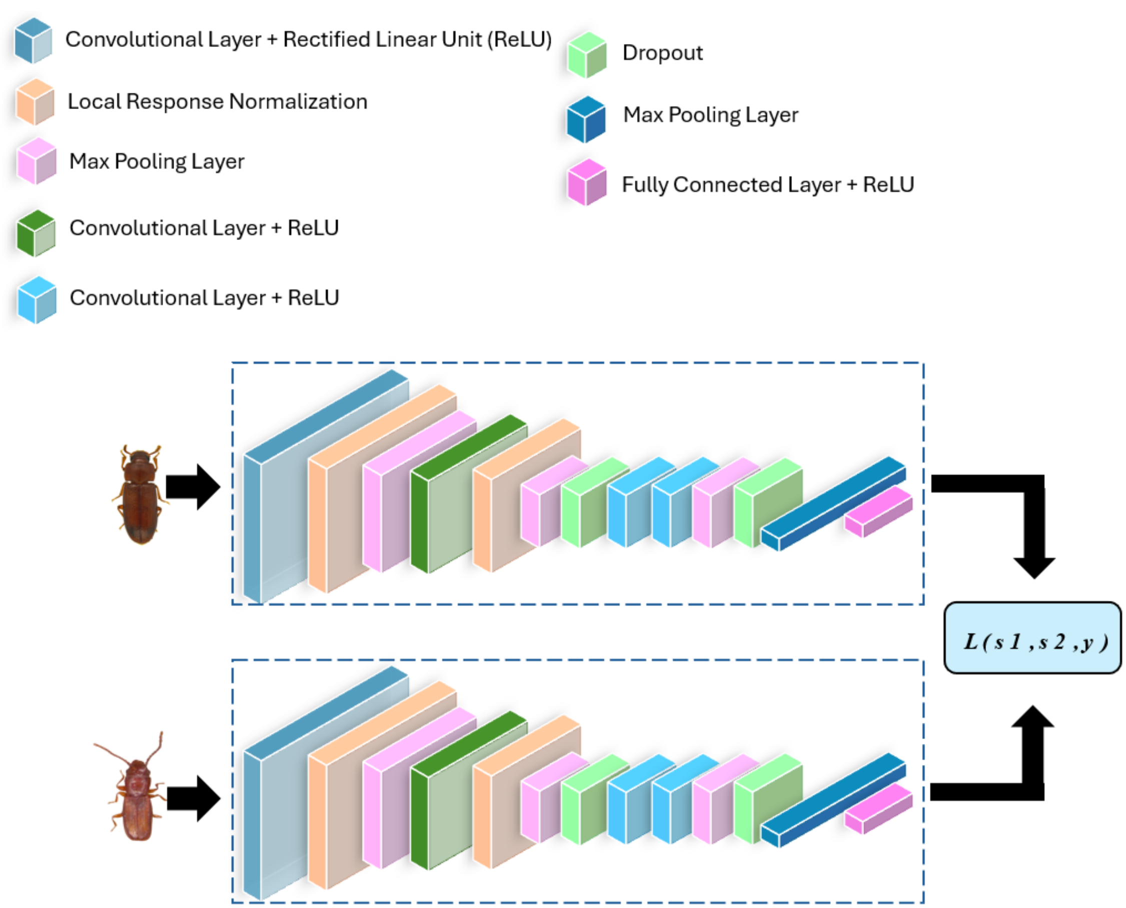


Figure 7. Proposed model structure using the Siamese Neural Network.

Neural Network Architecture:

Siamese Architecture: Implement a Siamese Neural Network comprising two identical sub-networks that share weights. Each sub-network should include several convolutional and pooling layers followed by a few fully connected layers as shown in Figure 7.

4. Training the Model

Setup:

Training Data: Use a split of 70% of the image pairs for training, and 30% for testing.

Hyperparameters: Set an appropriate learning rate, number of epochs, and batch size based on preliminary experiments.

Below are the descriptions of the robust parameters used for this SNN.

1. Convolutional Layers: Convolutional layers enable neural networks to analyze and interpret images by extracting key features such as edges and textures, similar to how human vision processes visual information. These layers use filters that systematically identify and integrate these details, enhancing the network's ability to perform tasks like image classification and object detection.

First Convolutional Layer: Reduce to 7x7 filters with 128 filters.

Second Convolutional Layer: Use a 5x5 filter with 256 filters.

Third Convolutional Layer: Further reduce to 3x3 filters with 512 filters.

2. Pooling Layers: Pooling layers reduces the dimensionality of data by combining the outputs of neuron clusters at one layer into a single neuron in the next layer, which simplifies the computational load and enhances the network's ability to detect features in an image. This process, often referred to as downsampling, helps the neural network become more efficient and less sensitive to the exact location of features.

A **2x2 max pooling layers** with a stride of 2 after each convolutional layer to reduce spatial dimensions while retaining important features.

3. Dropout: Dropout layers help prevent overfitting in neural networks by randomly deactivating a subset of neurons during training, forcing the network to learn more robust features that are not reliant on any small set of neurons. This technique improves the network's generalization ability, making it perform better on new, unseen data.

A **dropout of 0.3 rate** after each pooling layer is used to prevent overfitting.

4. Fully Connected Layers: Fully connected layers in a neural network link every neuron in one layer to every neuron in the preceding layer, which allows the network to integrate learned features from prior layers into a final output. This comprehensive connection pattern helps the network make decisions based on the complete and integrated data it has processed.

Fully Connected Layer: **1024 neurons**.

5. Local Response Normalization: Local Response Normalization (LRN) is a technique used in neural networks to help increase the model's generalization by normalizing the responses across multiple computed features. This process reduces the response of strongly activated neurons, thereby promoting model robustness and reducing the likelihood of neurons becoming overly dependent on strong activations, which mimics a form of lateral inhibition found in biological neurons.

A **Local Response Normalization** with **Batch Normalization** was used after each convolutional layer to stabilize learning and improve convergence rates.

6. Learning Rate: The learning rate is a critical parameter in the training of neural networks that determines the size of the steps the model takes during optimization of its weights. A well-chosen learning rate helps ensure efficient training; too large might cause the training to diverge, while too small could result in a long training process or the model getting stuck in local minima.

Start with a **learning rate of 0.001** and consider implementing learning rate schedules or decay to adjust the learning rate dynamically based on the training progress.

7. Training Epochs and Batch Size: Training epochs refer to the number of complete passes through the entire training dataset that a neural network makes during its learning process. Batch size, on the other hand, defines the number of training examples used to calculate the gradient during a single update of the model's weights, influencing both the speed and stability of the learning process.

The number of epochs was **100** with a batch size of **32** to ensure sufficient learning without overfitting.

8. Regularization Techniques: Regularization techniques are methods used in training neural networks to prevent overfitting, ensuring the model performs well on new, unseen data, the L2 encourages the network to keep the weights small, leading to a simpler and more generalizable model.

Besides dropout, an **L2** regularization was added to the weights of the network to further control for overfitting.

9. Simulation:

Training Process: Train the network using the training set with validation checks to monitor performance and prevent overfitting.

Model Adjustments: Fine-tune the network based on validation performance, adjusting layers, learning rates, and other parameters as necessary.

5. Evaluation and Validation

Performance Metrics:

Accuracy: Measure the accuracy of the model on the testing set to evaluate its effectiveness in distinguishing between beetle species.

Precision and Recall: Calculate precision and recall for each species to understand model performance in identifying specific species.

Statistical Validation:

Confusion Matrix: Use a confusion matrix to visually assess model performance across different species classifications.

Discussion of results.

Confusion Matrix

Confusion matrices are used to present the performance evaluation of our beetle classification model. As shown in Figure 8, these matrices illustrate the model's accuracy in distinguishing between red flour beetles and rusty grain beetles during both training and testing phases.

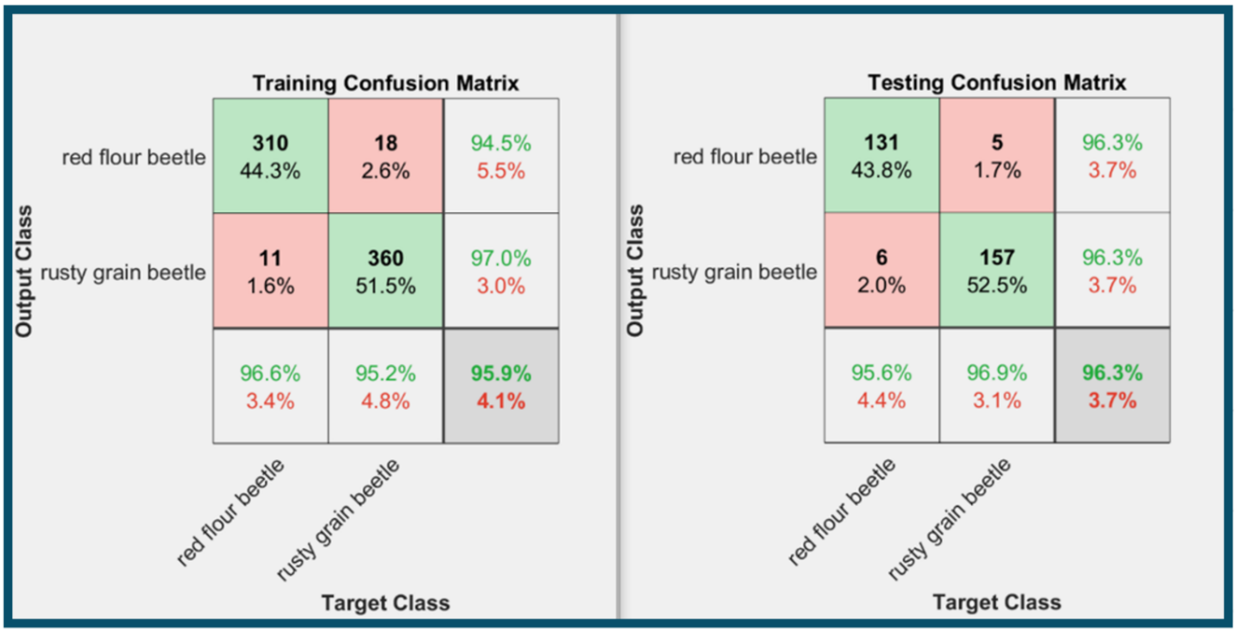


Figure 8 . Training and Testing Confusion Matrices for the Dopplergangger Beetle Classification Model.

1. Training Confusion Matrix Interpretation:

True Positives (TP) for Red Flour Beetle: 310 instances were correctly classified as red flour beetles, which is 44.3% of the training data.

False Positives (FP) for Rusty Grain Beetle: 18 instances of rusty grain beetles were incorrectly classified as red flour beetles, making up 2.6%.

False Negatives (FN) for Red Flour Beetle: 11 instances of red flour beetles were incorrectly classified as rusty grain beetles, which is 1.6%.

True Positives (TP) for Rusty Grain Beetle: 360 instances were correctly classified as rusty grain beetles, amounting to 51.5% of the training data.

The percentages in the bottom row (96.6%, 95.2%) represent the recall or true positive rate for each class, indicating a high level of sensitivity in classification. The rightmost column percentages (95.9%, 97.0%) show the precision or positive predictive value, demonstrating the model's accuracy when it predicts a certain class.

2. Testing Confusion Matrix Interpretation:

True Positives (TP) for Red Flour Beetle: 131 instances were correctly classified, representing 43.8% of the testing data.

False Positives (FP) for Rusty Grain Beetle: 5 instances were mistakenly labeled as red flour beetles, which is 1.7%.

False Negatives (FN) for Red Flour Beetle: 6 instances were wrongly labeled as rusty grain beetles, accounting for 2.0%.

True Positives (TP) for Rusty Grain Beetle: 157 instances were correctly identified, comprising 52.5% of the testing data.

The recall rates for the testing data (95.6%, 96.9%) indicate the model's effectiveness in identifying true positives. The precision values (96.3% for both classes) on the testing set are also quite high, signifying the model's high accuracy when a prediction is made.

Both matrices demonstrate the model's robust performance, as indicated by the high precision and recall values. This suggests that the model is highly effective at accurately classifying the beetle species, with little misclassifications.

Conclusion

The Siamese Neural Network (SNN) achieved exceptional accuracy in addressing the "Beetle Doppelgängers" issue in this study. It demonstrated precision and recall rates over 95% in both training and testing datasets, effectively differentiating between the red flour and the rusty grain beetles. The SNN's capacity to detect and evaluate minor morphological subtleties, often overlooked by standard classification methods, is indicated by its high degree of accuracy, despite there being a slight decrease during the testing phase. The SNN's resistance to incorrect identifications and its capacity to handle subtle characteristics of beetles highlights its promise as an advanced tool for entomological classification, representing a substantial advancement in pest control and the preservation of biodiversity. Certainly, the SNN technique represents a significant advancement in species identification, offering the promise of improved precision and effectiveness in ecological and agricultural contexts.

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References

Brarathi, V. S. K., et al (2023). “Biology, Ecology, and Behavior of Rusty Grain Beetle (Crytolestes ferrugineus (Stephens)).” Insects.

Bookwalter, J. D., et al. (2023). " Understanding the Coleoptera community at the tree-line using taxonomic and functional guild approaches." Agricultural and Forest Entomology.

Campbell, J. F. (2003), “Patch exploitation by female red flour beetles, tribolium castaneum.” Journal of insect science.

Jian, F., et al (2006). “Vertical movement of adult rusty grain beetles, Cryptolested ferrugineus, in stored corn and wheat at uniform moisture content.”Journal of Insect Science

Malhotra, A. et al (2023). "Single-shot image recognition using Siamese Neural Networks." Proceedings of the 3rd International Conference on Advance Comting and Innovative technologies in Engineering.

Krinsky, W. L. (2019), Bettles “Coleoptera.” Medical and Veterinary Entomology, 3rd Edition.

LeCun, et al. (2016). "Deep Learning." Nature.

Ng’endo, R. N. et al (2013). "DNA barcodes for species identification in the Hyperdiverse Ant Genus *Pheidole* (Formicidae: Myrmicinae)." Journal of Insect Science.

Steiner, D., et al (2023). “Dynamic images comparison using Siamese neural network.” Proceedings of the 2023 International Conference on Software, Telecommunications and Computer Networks.