PROGRESS IN DEVELOPING A BARK BEETRLE IDENTIFICATION TOOL

G. Christopher Marais[1*], Isabelle C. Stratton[1], Andrew J. Johnson[1], Jiri Hulcr[1]

[1]School of Forest, Fisheries, and Geomatic Sciences, University of Florida, Gainesville, Florida, United States of America

*Corresponding author

E-mail: gmarais@ufl.edu

Abstract

This study presents a tool for the identification of bark beetles. These pests are known for their potential to cause extensive damage to forests globally, as well as for uniform and homoplastic morphology which poses identification challenges. Utilizing a MaxViT-based deep learning model is an innovative approach to classify bark beetles down to the species level from images containing multiple beetles. The methodology involves a comprehensive process of data collection, preparation, and model training, leveraging pre-classified beetle species to ensure accuracy and reliability. The model's high F1 score estimates of 0.99 indicates its exceptional performance, demonstrating a strong ability to accurately classify species, including those previously unknown to the model. This makes it a valuable tool for applications in forest management and ecological research. Despite the controlled conditions of image collection and potential challenges in real-world application, this study provides the first model capable of identifying the bark beetle species, and by far the largest training set of images for any comparable insect group. We also designed a function that reports if a species appears to be unknown. Further research is suggested to enhance the model's generalization capabilities and scalability, emphasizing the integration of advanced machine learning techniques for improved species classification and the detection of invasive or undescribed species.

Introduction

Computer vision technologies for the purposes of classification and identification are becoming progressively more prevalent in ecological research, biological systematics, and biosecurity. This is mainly attributable to the application of deep learning techniques, with convolutional neural networks (CNNs) and transformer networks being particularly influential (1,2). These methodologies have facilitated the emergence of hybrid architectures like MaxViT, which integrates the strengths of both CNNs and transformers to improve performance and efficiency, especially in contexts characterized by constrained data resources (3).

In ecological studies, deep learning models have demonstrated potential by accurately identifying species that are visually similar. These models excel in consistent, reliable, and accurate classifications even among closely resembling species. This capability underscores the technology's potential in ecology, biosystematics, and invasive species detection where precise species identification is crucial (4–9).

Bark beetles, an abundant and widespread group of wood boring insects, are notable for their potential to cause significant tree mortality. Their outbreaks are increasing particularly in scenarios where non-native species invade a region with naive hosts, or when the tree hosts are stressed and lessen their defense abilities, often because of climate change (10) The importance of detecting and accurately identifying these beetles cannot be overstated for forestry industries; however, existing identification methods fall short in efficiency and scale, posing challenges in safeguarding forests worldwide against infestations.

Bark and ambrosia beetles, encompassing the subfamilies Scolytinae and Platypodinae within the Curculionidae family, represent a diverse group with over 6000 species spanning approximately 250 genera across 26 different tribes (11). Although most bark beetle species are not typically categorized as pests, certain species can cause significant forest damage (12). This uneven degree of damage makes species-level critical: some species can trigger a region-wide regulatory action, while others with a very similar morphology are entirely harmless.

Global trade and travel have facilitated the spread of invasive species, enhancing the risk posed by these beetles (13).

The ecological impact of bark beetles is significant, as they alter habitats and affect numerous organisms (14). Damage caused to forests also have a notable economic impact on the pulp, paper, and timber industries (15). Economically, the damage inflicted on forests impacts industries like pulp, paper, and timber, with the southern pine beetle alone causing an estimated annual loss of around $43 million in the U.S. South (16). The increasing prevalence of bark and ambrosia beetles, exacerbated by climate change and international trade, highlights the urgent need for effective management strategies.

The monitoring, detection and identification of current and future bark beetle pests poses a significant challenge due to their small size, morphological homogeneity, and high variability within species (17–19). Traditional methods of identification, such as visual classification, require considerable expertise and are time-consuming. Molecular methods, like DNA sequencing, are impractical for large-scale pest detection efforts due to their slow processing and high costs (20).

Currently, federal, and state-level programs like the Cooperative Agricultural Pest Survey (About the CAPS Program | CAPS, 2023) and the USDA Forest Service's Early Detection and Rapid Response program (22) are dedicated to monitoring and identifying invasive pests. However, these methods are hindered by lengthy delays in identification and are prone to human error. Additionally, the conventional practice of discarding samples post-identification results in significant data loss, impeding the development of comprehensive reference collections.

The integration of artificial intelligence into identification workflows presents a promising solution to expedite and enhance the accuracy of bark beetles and many other important organismal groups (23). This study tests a deep learning model capable of classifying bark beetles down to the species level from images of multiple beetles at a time. We specifically focused on the development of model that could be used in practical, existing identification applications which typically deal with multi-species and multi-specimen samples. We tested a model structure that first disaggregates compound photographs, and then identifies individual beetle specimens. To train the model, we also devised a method for efficiently generating aggregate photos of multiple individuals, yielding the largest bark beetle photo collection ever assembled. In addition, we also devised a method for determining a probability that a species is “unknown” (absent in the training set), which is important in detecting novel species.

Methods

Images were collected by photographing physical bark beetle samples that have previously been classified according to species by bark beetle taxonomists using current

classification strategies (24). The selection of the beetle species for the model training was based on three factors. Firstly, their economic importance was a key consideration, ensuring inclusion of beetles with significant impact across various industries and ecosystems. Secondly, accessibility of physical samples was ensured. Lastly, consideration was given to the prevalence of these species in traps of the national pest monitoring networks, where the model may be helpful in the future.

Training set generation

The 12 selected species of pre-classified bark beetles were stored in 70% ethanol at -80°C before and after photography. During image collection the samples were placed in petri dish on a white background and submerged in 70% ethanol. Multiple bark beetles were included in a single image using a macro photography technique designed to optimize reproducibility of the image capturing process and image quality (Bark and Ambrosia Beetle Macro Photography for an AI Training Dataset, 2024). This approach to capturing images of multiple beetles at once sped up image collection compared to capturing one image of a beetle at a time. Each batch of beetle samples was of the same species to ease digital labelling. Each batch of beetle samples were also photographed 10 times over after agitating the peri dish between photographs. This was to increase the number of visual angles for each individual beetle photographed.

Pictures were taken with a Canon EOS REBEL with a 60mm lens. We kept the ISO at 100 and used a ring flash to reduce the shadows around each beetle. Each image taken in this way resulted in an image of multiple beetles at a resolution of 3456 x 5184 with 72 dpi at 24-bit color depth. The images with multiple beetles in it will be referred to as a composite image. The intention was to keep the photography setup relatively

straightforward to enhance reproducibility in the future. All images were taken from the top down onto the beetles on a rig that held the camera. The white background was selected to control the background with a high contrast between the beetles to aid in data preparation and identifying individual beetles.

Data Preparation

The composite images of multiple beetle samples were split into multiple images. Resulting in multiple images one beetle sample in each image. This was done using the Scikit-Image python package. This task was not a part of the deep learning model because our focus remained on solving the bark and ambrosia beetle classification problem and not general object detection.

The first step in data preparation was to confirm that all images were in focus and had enough lighting. The composite images were split into test validation and training datasets. The test set was 20% of all the composite images, maintaining the ratio of species in the training data to avoid skewing the testing or training sample in that way (Figure 1). Thereafter the remaining 80% of the training data were split using 5-fold cross validation (26). This results in five replicates of the data to monitor for sampling biases. The image data was split along the composite images and replicates of each composite image to avoid cases where the same individual may be in both the testing (or validation) and training dataset.

Fig 1: Example of 5-fold Cross-validation.

Once the image data were split, the composite images were broken down into smaller images each containing a single beetle (Figure 2). This was done using the Scikit-Image package in python using the following steps (27).

1. Import color composite image.
2. Convert image to black and white.
3. Binarize the image with beetles as black and the background as white using the Otsu thresholding algorithm (28).
4. Remove any black objects that are in contact with the image edge.
5. Detect all black blobs in the image and draw rectangle boxes around each of them using the built-in label function from Scikit-Image.
6. Use K-means with 2 clusters separating objects by size
7. Keep only the larger objects.
8. Use the rectangle coordinates of kept objects and extract those sections from the original color image.

Fig 1: Splitting of Composite Image to Individual bark Beetle Images

Images that contained multiple beetles or contained only partial segments of beetles were manually removed from the data through visual inspection of all files. Images that contained any foreign bodies or organisms were also removed.

Model Training

We adopted a transfer learning approach for model training to reduce computation time and amount of data required to train the model effectively (29). We utilized a MaxViT

architecture that has 116.1 million parameters and 92.6 million activations, previously trained on a subset of the ImageNet-22K dataset, comprising over 14 million annotated images and 22 thousand labels (3,30). The pre-trained model was obtained through the Pytorch Image Models (timm) package on Hugging Face (31). Specifically, it was trained on the ImageNet-12K subset, consisting of 1.2 million images across 11,821 classes, and thereafter it was further fine-tuned on the ImageNet-1K subset, containing 1.2 million images with 1000 classes.

We opted for the MaxViT model architecture to leverage its blend of global and local attention mechanisms (3), predominantly employing the Adam optimizer (32). The model utilizes various activation functions like ReLU, SiLU, and GELU (3,33), with Tanh being crucial in the linear classification head. In the classification layer, the model processes the feature map into a vector of 75,264 values, which is then reduced to a vector of length corresponding to the number of classes (12 in our case, corresponding to the number of beetle species). The Tanh function produces values between -1 and 1, which are converted into prediction probabilities using SoftMax (34). This ensures that the output probabilities sum up to 1 for all classes. The consistent label smoothing cross-entropy loss function was applied to estimate the error (loss) for all models (35), this specific objective function was chosen for its suitability in multi-class classification tasks like ours. This loss function also serves as a regularization method, mitigating overfitting and enhancing model performance and generalization by introducing slight label noise to the training data (36).

The pretrained and fine-tuned MaxViT model was further trained on our images that had dimensions of 224 x 224 pixels to suit the resolution that the model was pre-

trained on. The conversion was carried out using the Pytorch and FastAI packages in python (37,38).

To artificially increase the size and diversity within the training data and to prevent overfitting to our data and improve generalization of the model we used image augmentations (Shorten & Khoshgoftaar, 2019). Each of these augmentations were applied to a random degree during the training process with a probability of 0.8 to be applied to any image in each batch. The augmentations we made included gaussian blur and random patches of noise. Additionally, we performed changes to the rotation, flip, brightness, contrast, zoom, scaling, warping, and cropping of images as augmentations.

During training we replaced the existing classification head of the model with our own classification head with one node for each class (12 nodes in total). The model then went through a warm-up phase of one epoch of training where the layers of the model were all kept frozen excluding the classification head (40). Thereafter the model was trained for several additional epochs where no layers were frozen until validation loss of the model plateaued and converged with the training loss (Figure 3).

The next step was to identify the ideal set of hyperparameters to train our model with. To do this we made use of the Hipergator supercomputer at the University of Florida. During hyperparameter tuning, we utilized PyTorch and FastAI for GPU-accelerated model training, employing the Weights and Biases (WandB) package for overseeing parameter optimization (41). Bayesian search was employed to expedite parameter optimization instead of exhaustive grid search. The Hyperparameters investigated included batch size, epochs (excluding the warm-up phase epoch), and learning rate. These were selected based on their impact on the validation loss. After evaluating various

models, a batch size of 64, trained for 5 epochs with a learning rate of 0.003, was chosen. These hyperparameters were subsequently utilized for all experiments and training of the parameters for the final model.

Fig 3: Training Loss (blue) and Validation Loss (orange) Across Epochs for Best Model During Parameter Tuning. The x-axis represents the number of epochs, and the y-axis represents the calculated loss.

For each evaluated image, the model generates probabilities for each of the 12 classes, corresponding to specific beetle species. However, it lacks the ability to classify unknown species. Training a class of entities unknown to the model would require impractical amounts of training data. A common alternative for detecting unknown classes is to apply a decision threshold on the existing probabilities which determines whether an output is classified as unknown or known. However, this approach does not produce a probability of how confident the model is that the class is unknown (42).

To address this limitation, we propose a formula to estimate the probability of the unknown class based on the distribution of probabilities of trained classes, aiming to provide users with additional information for decision-making during deployment.

Let P be a vector of length n representing the probabilities of n classes. Let t be a scalar representing the value of the threshold we use in our algorithm to represent the decision boundary. We define the probability P_u as the unknown class or out-of-class probability (Equation 1). Where d is a vector of length n representing each probability P to the power of the compliment of the absolute difference between each of the probabilities P and the threshold t (Equation 2).

$$P_u = 1 - \frac{\sum_{j=1}^{n} \sum_{l=1}^{n} |d_i - d_j|}{2(n-1) \sum_{j=1}^{n} d_i} \#(1)$$

$$d = P_i^{(1-|P_i - t|)} \#(2)$$

This formula generates an estimate probability that an image belongs to the unknown class as a function of how much higher a single probability in the vector is than the other probabilities and whether it is above the threshold parameter. The ideal vector has one high probability, above the threshold, and the rest of the probabilities are very low. This will produce a low P_u close to 0 unknown class probability estimate because the classifier seems to be certain that one class is the true class. However, if a vector is produced with multiple probabilities that are all very similar the unknown class probability will be closer to 1. This makes it possible to produce an estimate of the unknown probability and represent it in an output alongside the class probabilities as a measure of certainty of the classifier without sacrificing the ability to use a threshold on the original output of the model for out-of-class classification.

The code to this model and a demonstrative version of the bark beetle image classifier are available for public access on GitHub (https://github.com/UF-Forest-Entomology-Lab/Bark_Beetle_Classification) and Hugging Face Spaces (https://huggingface.co/spaces/ChristopherMarais/Andrew_Alpha), respectively.

Results

The model demonstrated near perfect accuracy in identifying bark beetle species, achieving F1-scores of 0.99 on our validation dataset and a perfect 1.0 on our testing dataset.

We accumulated 2 290 composite images of 12 species (Figure 4). We were able to obtain an average of 12.9 single beetle images from each composite image (Figure 6). The average number of single beetle images per composite image differed markedly between species (range: 1248-4968, Figure 5). This was because the beetles were all different sizes, and it wasn't possible to fit the same number of beetles in each composite image.

Fig 4: Number of Composite Images Collected per Species

Fig 5: Number of Single Beetle Images Generated per Species

Fig 6: Average Number of Single Beetle Images per Composite Image by Species

After settling on a batch size of 64 images with a pre-trained model, and 5 epochs with a learning rate of 0.003, these parameters were used for further training, evaluation, and testing. To evaluate the model thoroughly we used 5-fold cross validation. This meant that for every fold we evaluated the model a different subset of the data covering all the training data across all folds. For each fold the model was also evaluated on the holdout testing data. To evaluate the model, we made use of F1-score instead of a general accuracy score. The F1 score is more suited to multi-class classification as it is more sensitive to data distribution (43). An F1-score ranges between 0 and 1 with higher values

indicating better classification. The F1-score obtained for the model averaged over all the folds for the validation data was 0.99 and for the testing data was 1.0.

To estimate our model's performance on out-of-class classification with our unknown class probability formula we chose to test it on images that are closely related to the training data, but not included in the training data. This was done by training multiple models each with one class of beetles excluded from the training data. Thus 12 different models, each of which has been trained only on data of 11 classes and excluding one class. The excluded class was still used to evaluate and test the model as and represented a true label of "unknown". This was repeated for each of the 5 folds to get a robust estimate of performance. Therefore, a total of 60 models were all trained using the originally optimized set of parameters. For each model we then applied the standard threshold decision boundary method of out of class classification to test the ability of the model to identify an unknown class. The same was repeated using our own unknown class probability formula to estimate the probability that an image belonged to an unknown class. Thereafter the class with the highest probability was selected as the classified class.

Both the conventional decision boundary approach and our unknown class formula approach add an additional threshold parameter to the inference process. This threshold parameter can be optimized by using the Receiver Operating Characteristic (ROC) curve. A ROC curve is a plot that shows the performance of a model at various threshold values. This plot compares the True Positive Rate (TPR) to the False Positive Rate (FPR). The TPR is a synonym for recall and is the ratio of true positives to the sum of true positives and false negatives. The FPR is the ratio of the false positives to the sum of false positives

and true negatives. We calculated the FPR and TPR for the unseen testing data and the validation data for each model. We took the average of the ROC curves for each fold and compared them. We decided to take a One-vs-Rest approach on the ROC curve with the unknown class as the positive class and all other classes as the negative class(44).

The ROC and the conventional thresholding approach perform similarly both close to the ideal curve and far from the random curve (Figure 7). The ideal curve is in the top left corner with a TPR of 1 and a FPR of 0. The ideal area under the curve (AUC) is therefore 1. The conventional threshold decision boundary approach comes close with an AUC of 0.981 and our own formula approach is very similar with an AUC of 0.982. This means that both methods work well at classifying an unknown class. The optimal threshold can be obtained as the point on the plot that is closest to the 1 TPR and 0 FPR point. Both methods suggest an optimal threshold of 0.8 (Figure 7).

To get an estimate of how well the model performs in general when using this threshold, we calculated the weighted F1-score using the threshold. This gave us an F1-score of 0.97 for our formula and an F1-score of 0.98 for the conventional decision thresholding approach when applied to the unseen testing data.

Fig 7: ROC curves of our out-of-class algorithm (blue) and a threshold decision boundary (red) representing the true positive rates (TPR) compared to the false positive rates (FPR) for test data classification results across all folds. The Diagonal (black) line represents the performance of a random binary classifier.

Discussion

In this study, we developed an advanced tool for identifying bark beetles, a significant threat to forestry due to their potential for extensive tree mortality. The need for efficient and accurate identification methods is underscored by the limitations of current approach, which relies almost entirely on trained personnel, which is difficult to scale globally to the level of need. By leveraging a deep learning model, specifically a MaxViT architecture capable of classifying bark beetles down to the species level from images, the study represents a significant leap forward. The methodology involved collecting images of pre-classified beetle species, which were then used to train the model through a rigorous data preparation and model training process. This approach not only promises to enhance identification accuracy but also addresses the challenges posed by traditional identification methods. The model was evaluated using F1 scores and showed notable accuracy. In addition, its ability to classify unknown species makes this approach even more promising for bark beetle detection and research.

These high identification scores reflect the model's precision and reliability in species classification across varied datasets. Additionally, the model's performance in out-of-class classification shows its potential to diagnose unforeseen beetle infestations. The high accuracies could be attributed to the model's advanced machine learning architecture and the comprehensive dataset on which it was trained, allowing for nuanced differentiation between species.

Several features of the model requires further testing before deployment in real-world scenarios with higher noise levels and greater variability in image data. Our training set collection and preparation involved the photography of beetle samples within a

controlled environment, which may not faithfully replicate the diverse conditions encountered in natural settings. Moreover, the process of obtaining single beetle images from composite images, integral to preprocessing, was based on a rudimentary algorithm, therefore the model's use in scenarios with complex or varied backgrounds will require further development of the disaggregation step.

Our study also contended with data imbalance issues, characterized by unequal image distribution among various beetle species. In theory such imbalance could lead to a model bias, favoring more frequently represented species, over lesser-represented species. However, this does not seem to have affected accuracy with our initial set of 12 species. The high F1-scores, while indicative of the model's performance, also raise the possibility of overfitting, particularly given the homogeneity of the training dataset. The methodology employed for out-of-class classification, focusing on unknown species identification, was based on a custom formula that relied on the distribution probabilities of known classes.

Concerns regarding scalability and data efficiency of the model were also noted, particularly in relation to incorporating new species into the dataset. For a model intended to identify a broad array of species in diverse environments, efficient data collection and processing capabilities are imperative.

Additionally, reliance on pre-trained models, while beneficial in some respects, introduces the risk of inheriting biases from the source datasets.

Considering these limitations, we propose several directions for future research to enhance the model's practicality and scientific utility. Expanding the number of species the model is trained on and improving data efficiency are crucial steps. A significant focus

364 should be placed on refining the object detection algorithm to improve accuracy,
365 particularly for images with higher noise levels.

366 To enhance the model's capabilities further, a multifaceted approach involving the
367 integration of advanced machine learning techniques can be considered. A pivotal
368 enhancement would be the integration of out-of-class classification directly into the
369 network's classification head. This integration is crucial as it would enable the model to
370 identify and categorize species that were not part of the original training set, effectively
371 recognizing 'unknown' or novel classes. By doing so, the model would not only classify
372 known species with high accuracy but also flag species that are beyond its current
373 knowledge base. This feature is important since in practice, encountering unclassified or
374 new species is common.

375 In addressing the challenges posed by data gaps and underrepresented species,
376 the incorporation of generative components into the model could be transformative. This
377 approach would involve using techniques like Generative Adversarial Networks (GANs)
378 or Variational Autoencoders (VAEs) to synthesize training data for species that are not
379 sufficiently represented in the existing dataset. This method could significantly enhance
380 the model's training process (45).

381 Another significant enhancement could be realized by adopting a self-supervised
382 contrastive learning approach (46). By applying this approach, the model can learn from
383 unlabeled data, which is a common challenge in ecological datasets where labeling can
384 be resource-intensive and time-consuming. This approach enables the model to develop
385 a more nuanced understanding of the features that distinguish one species from another,
386 even in the absence of explicit labels. Finally, field deployment of the model warrants

investigation, ensuring that it is non-disruptive and user-friendly. Such deployment is essential for evaluating the model's real-world applicability and effectiveness.

In summary, while our model demonstrates significant promise in beetle species classification, addressing these noted limitations and pursuing the suggested avenues for future research are pivotal for enhancing the model's scientific robustness and applicability in diverse ecological settings.

Conclusion

A dual-pronged approach, combining advanced machine learning techniques with a comprehensive data management strategy, enabled us to classifying morphologically cryptic and mutually similar bark and ambrosia beetle species. Central to our methodology was the deployment of a MaxViT-based machine learning model, optimized for beetle image analysis.

To augment the model's utility and scientific contribution, future research should focus on diversifying the training dataset, refining the object detection algorithm, incorporating additional advanced machine learning techniques and generative components, and exploring self-supervised contrastive learning approaches.

In summary, while our model and data management solutions were not without limitations, they offer a path forward in the development of fast and accurate identification of cryptic biological objects in high-throughput settings.

REFERENCES

1. Dosovitskiy A, Beyer L, Kolesnikov A, Weissenborn D, Zhai X, Unterthiner T, et al. An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. ICLR 2021 - 9th International Conference on Learning Representations [Internet]. 2020 Oct 22 [cited 2024 Jan 15]; Available from: https://arxiv.org/abs/2010.11929v1

2. Lecun Y, Bengio Y, Hinton G. Deep learning. Nature 2015 521:7553 [Internet]. 2015 May 27 [cited 2024 Jan 15];521(7553):436–44. Available from: https://www.nature.com/articles/nature14539

3. Tu Z, Talebi H, Zhang H, Yang F, Milanfar P, Bovik A, et al. MaxViT: Multi-Axis Vision Transformer. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) [Internet]. 2022 Apr 4 [cited 2023 Jun 19];13684 LNCS:459–79. Available from: https://arxiv.org/abs/2204.01697v4

4. Badirli S, Picard CJ, Mohler G, Richert F, Akata Z, Dundar M. Classifying the unknown: Insect identification with deep hierarchical Bayesian learning. Methods Ecol Evol [Internet]. 2023 Jun 1 [cited 2024 Feb 29];14(6):1515–30. Available from: https://onlinelibrary.wiley.com/doi/full/10.1111/2041-210X.14104

5. Cheng X, Zhang Y, Chen Y, Wu Y, Yue Y. Pest identification via deep residual learning in complex background. Comput Electron Agric. 2017 Sep 1;141:351–6.

6. Marques ACR, Raimundo MM, Cavalheiro EMB, Salles LFP, Lyra C, Von Zuben FJ. Ant genera identification using an ensemble of convolutional neural networks. PLoS One [Internet]. 2018 Jan 1 [cited 2024 Feb 29];13(1):e0192011. Available from: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0192011

7. Wäldchen J, Mäder P. Machine learning for image based species identification. Methods Ecol Evol [Internet]. 2018 Nov 1 [cited 2024 Feb 29];9(11):2216–25. Available from: https://onlinelibrary.wiley.com/doi/full/10.1111/2041-210X.13075

8. Kasinathan T, Singaraju D, Uyyala SR. Insect classification and detection in field crops using modern machine learning techniques. Information Processing in Agriculture. 2021 Sep 1;8(3):446–57.

9. Bjerge Id K, Alison J, Dyrmann M, Frigaard CE, Mann HMR, Høye TT. Accurate detection and identification of insects from camera trap images with deep learning. PLOS Sustainability and Transformation [Internet]. 2023 Mar 15 [cited 2024 Feb 29];2(3):e0000051. Available from: https://journals.plos.org/sustainabilitytransformation/article?id=10.1371/journal.pstr.0000051

10. Klepzig KD, Adams AS, Handelsman J, Raffa KF. Symbioses: A Key Driver of Insect Physiological Processes, Ecological Interactions, Evolutionary Diversification, and Impacts on Humans. Environ Entomol [Internet]. 2009 Feb 1 [cited 2023 Dec 5];38(1):67–77. Available from: https://dx.doi.org/10.1603/022.038.0109

11. Pistone D, Gohli J, Jordal BH. Molecular phylogeny of bark and ambrosia beetles (Curculionidae: Scolytinae) based on 18 molecular markers. Syst Entomol [Internet]. 2018 Apr 1 [cited 2023 Jun 17];43(2):387–406. Available from: https://onlinelibrary.wiley.com/doi/full/10.1111/syen.12281

12. Heliövaara K, Peltonen M. Bark Beetles in a Changing Environment. Ecological Bulletins. 1999;47.

13. Brockerhoff A M Liebhold EG, Brockerhoff EG, Liebhold AM. Ecology of forest insect invasions. Biol Invasions. 2017;19:3141–59.

14. Morris JL, Cottrell S, Fettig CJ, Hansen WD, Sherriff RL, Carter VA, et al. Managing bark beetle impacts on ecosystems and society: priority questions to motivate future research. Journal of Applied Ecology [Internet]. 2017 Jun 1 [cited 2023 Jun 17];54(3):750–60. Available from: https://onlinelibrary.wiley.com/doi/full/10.1111/1365-2664.12782

15. Grégoire JC, Raffa KF, Lindgren BS. Economics and Politics of Bark Beetles. Bark Beetles: Biology and Ecology of Native and Invasive Species. 2015 Jan 1;585–613.

16. Holmes T, Koch F. Bark Beetle Epidemics, Life Satisfaction, and Economic Well-Being. Forests 2019, Vol 10, Page 696 [Internet]. 2019 Aug 16 [cited 2023 Jun 17];10(8):696. Available from: https://www.mdpi.com/1999-4907/10/8/696/htm

17. Hulcr J, Dunn RR. The sudden emergence of pathogenicity in insect–fungus symbioses threatens naive forest ecosystems. Proceedings of the Royal Society B: Biological Sciences [Internet]. 2011 [cited 2023 Dec 21];278(1720):2866–73. Available from: https://royalsocietypublishing.org/doi/10.1098/rspb.2011.1130

18. Kirkendall LR, Biedermann PHW, Jordal BH. Evolution and Diversity of Bark and Ambrosia Beetles. Bark Beetles: Biology and Ecology of Native and Invasive Species. 2015 Jan 1;85–156.

19. Vega FE, Hofstetter RW. Bark Beetles: Biology and Ecology of Native and Invasive Species. Bark Beetles: Biology and Ecology of Native and Invasive Species. 2015 Jan 8;1–620.

20. Jordal BH, Kambestad M. DNA barcoding of bark and ambrosia beetles reveals excessive NUMTs and consistent east-west divergence across Palearctic forests.

Mol Ecol Resour [Internet]. 2014 Jan 1 [cited 2023 Jun 17];14(1):7–17. Available from: https://onlinelibrary.wiley.com/doi/full/10.1111/1755-0998.12150

21. About the CAPS Program | CAPS [Internet]. [cited 2024 Feb 28]. Available from: https://caps.ceris.purdue.edu/about

22. Rabaglia RJ, Cognato AI, Hoebeke ER, Johnson CW, LaBonte JR, Carter ME, et al. Early Detection and Rapid Response: A 10-Year Summary of the USDA Forest Service Program of Surveillance for Non-Native Bark and Ambrosia Beetles. American Entomologist [Internet]. 2019 Mar 12 [cited 2024 Feb 28];65(1):29–42. Available from: https://dx.doi.org/10.1093/ae/tmz015

23. Høye TT, Ärje J, Bjerge K, Hansen OLP, Iosifidis A, Leese F, et al. Deep learning and computer vision will transform entomology. Proc Natl Acad Sci U S A [Internet]. 2021 Jan 11 [cited 2023 Jun 29];118(2):e2002545117. Available from: https://www.pnas.org/doi/abs/10.1073/pnas.2002545117

24. Hulcr J, Atkinson TH, Cognato AI, Jordal BH, McKenna DD. Morphology, Taxonomy, and Phylogenetics of Bark Beetles. Bark Beetles: Biology and Ecology of Native and Invasive Species. 2015 Jan 1;41–84.

25. Bark and Ambrosia Beetle Macro Photography for an AI Training Dataset [Internet]. [cited 2024 Feb 29]. Available from: https://www.protocols.io/private/609087D7B64611EE8CB80A58A9FEAC02

26. Bates S, Hastie T, Tibshirani R. Cross-validation: what does it estimate and how well does it do it? 2021 Apr 1 [cited 2023 Jun 18]; Available from: https://arxiv.org/abs/2104.00673v4

27. Van Der Walt S, Schönberger JL, Nunez-Iglesias J, Boulogne F, Warner JD, Yager N, et al. Scikit-image: Image processing in python. PeerJ [Internet]. 2014 Jun 19 [cited 2023 Jun 18];2014(1):e453. Available from: https://peerj.com/articles/453

28. Yousefi J. Image Binarization using Otsu Thresholding Algorithm. 2011 [cited 2023 Jun 18]; Available from: https://www.researchgate.net/publication/277076039

29. Weiss K, Khoshgoftaar TM, Wang DD. A survey of transfer learning. J Big Data. 2016;3(1).

30. Deng J, Dong W, Socher R, Li LJ, Kai Li, Li Fei-Fei. ImageNet: A large-scale hierarchical image database. 2010 Mar 1;248–55.

31. Wightman R. PyTorch Image Models. GitHub repository. GitHub; 2019.

32. Kingma DP, Ba JL. Adam: A Method for Stochastic Optimization. 3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings [Internet]. 2014 Dec 22 [cited 2023 Jun 19]; Available from: https://arxiv.org/abs/1412.6980v9

33. Dubey SR, Singh SK, Chaudhuri BB. Activation Functions in Deep Learning: A Comprehensive Survey and Benchmark. Neurocomputing [Internet]. 2021 Sep 29 [cited 2023 Jun 19];503:92–108. Available from: https://arxiv.org/abs/2109.14545v3

34. Glorot X, Bordes A, Bengio Y. Deep Sparse Rectifier Neural Networks. In: Gordon G, Dunson D, Dudík M, editors. Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics [Internet]. Fort Lauderdale, FL, USA: PMLR; 2011. p. 315–23. (Proceedings of Machine Learning Research; vol. 15). Available from: https://proceedings.mlr.press/v15/glorot11a.html

35. Müller R, Kornblith S, Hinton G. When Does Label Smoothing Help? Adv Neural Inf Process Syst [Internet]. 2019 Jun 6 [cited 2023 Jun 19];32. Available from: https://arxiv.org/abs/1906.02629v3

36. Xu Y, Xu Y, Qian Q, Li H, Jin R. Towards Understanding Label Smoothing. 2020 Jun 20 [cited 2023 Jun 19]; Available from: https://arxiv.org/abs/2006.11653v2

37. Paszke A, Gross S, Massa F, Lerer A, Bradbury J, Chanan G, et al. PyTorch: An Imperative Style, High-Performance Deep Learning Library. Adv Neural Inf Process Syst [Internet]. 2019 Dec 3 [cited 2023 Jun 18];32. Available from: https://arxiv.org/abs/1912.01703v1

38. Howard J, Gugger S. fastai: A Layered API for Deep Learning. Information (Switzerland) [Internet]. 2020 Feb 11 [cited 2023 Jun 18];11(2). Available from: http://arxiv.org/abs/2002.04688

39. Shorten C, Khoshgoftaar TM. A survey on Image Data Augmentation for Deep Learning. [cited 2023 Jun 18]; Available from: https://doi.org/10.1186/s40537-019-0197-0

40. Yosinski J, Clune J, Bengio Y, Lipson H. How transferable are features in deep neural networks? Adv Neural Inf Process Syst. 2014;27.

41. Biewald L. Experiment Tracking with Weights and Biases. 2020.

42. Sande SZ, Seng L, Li J, Agostino RD'. Statistical Learning in Medical Research with Decision Threshold and Accuracy Evaluation. Journal of Data Science

[Internet]. 2021 Sep 23 [cited 2023 Jun 19];19(4):634–57. Available from: https://jds-online.org/journal/JDS/article/1251/text

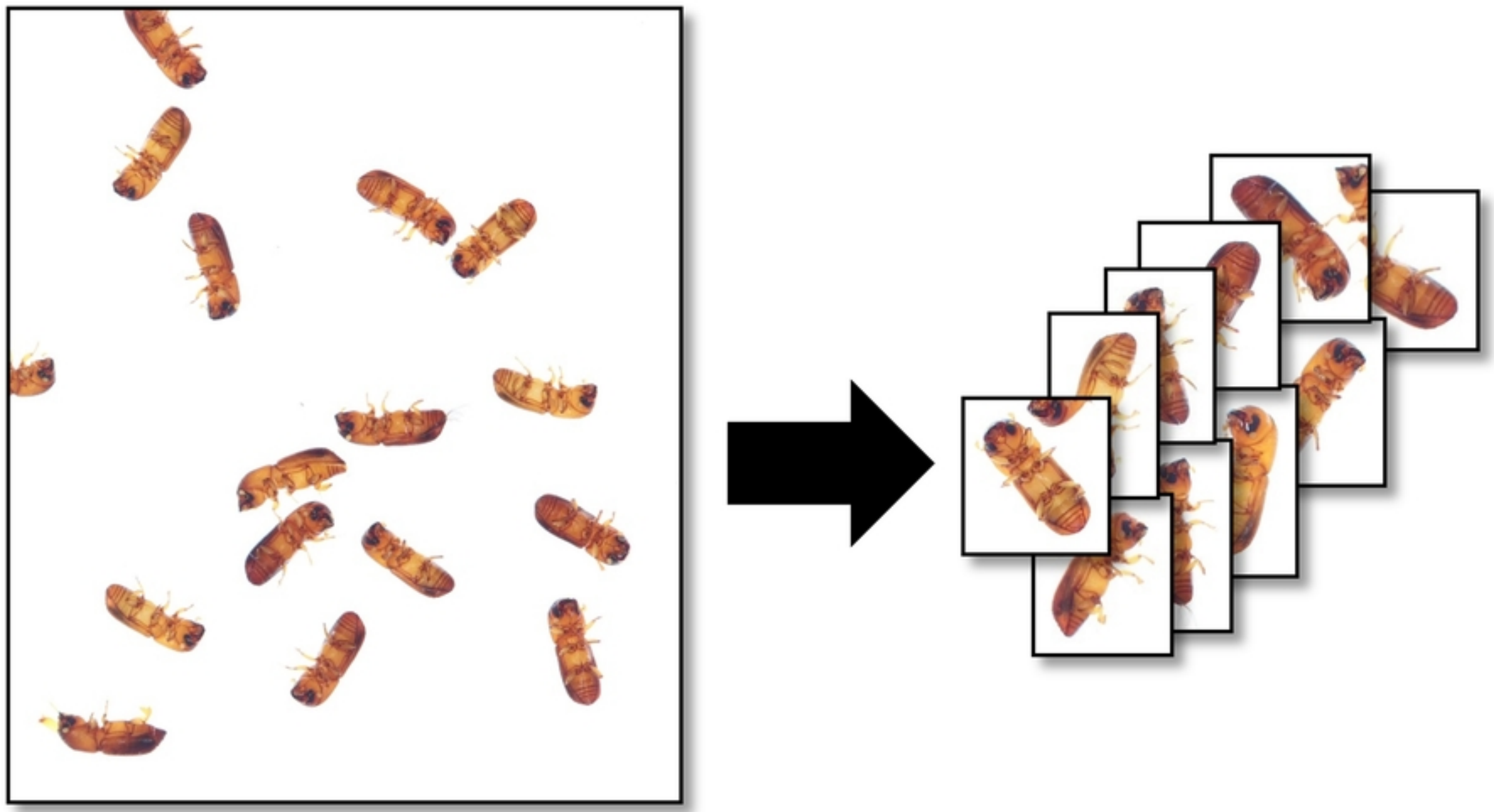
43. Takahashi K, Yamamoto K, Kuchiba A, Koyama T. Confidence interval for micro-averaged F 1 and macro-averaged F 1 scores. Applied Intelligence [Internet]. 2022 Mar 1 [cited 2023 Jun 24];52(5):4961–72. Available from: https://link.springer.com/article/10.1007/s10489-021-02635-5

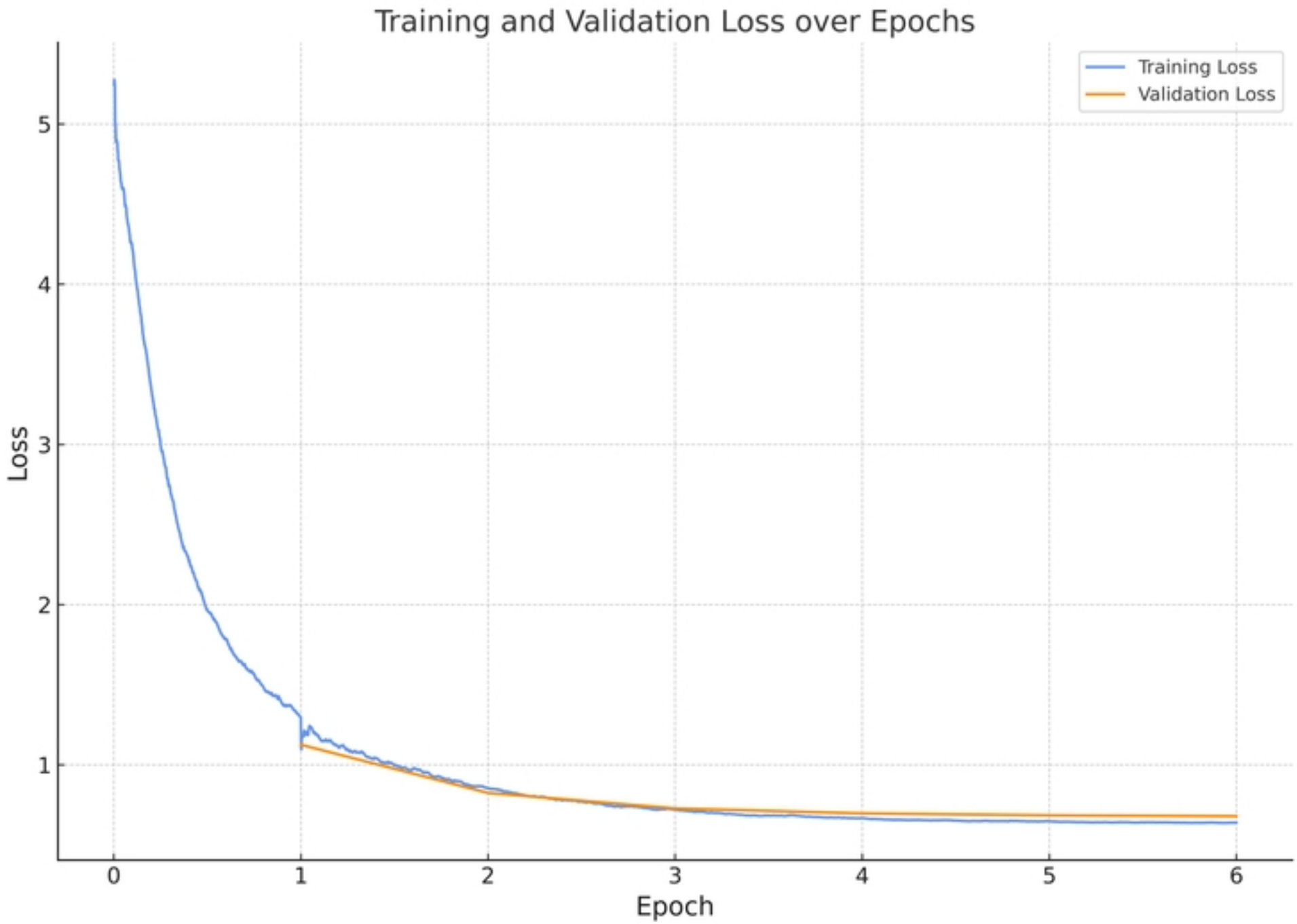
44. Jang J, Kim CO. Collective Decision of One-vs-Rest Networks for Open-Set Recognition. IEEE Trans Neural Netw Learn Syst. 2022;

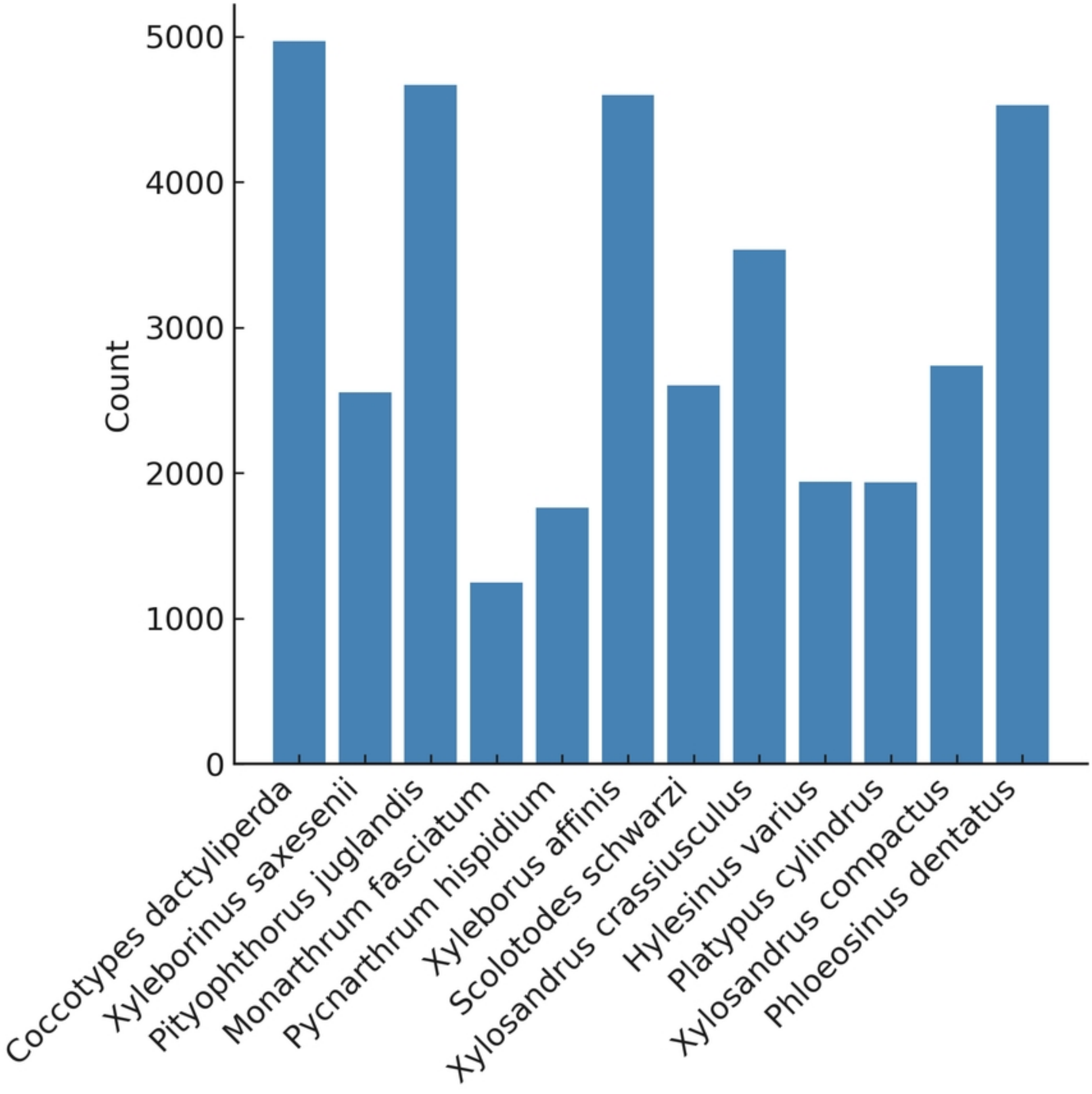
45. Yang L, Zhang Z, Song Y, Hong S, Xu R, Zhao Y, et al. Diffusion Models: A Comprehensive Survey of Methods and Applications. 2022 Sep 2 [cited 2023 Jun 27]; Available from: https://arxiv.org/abs/2209.00796v10

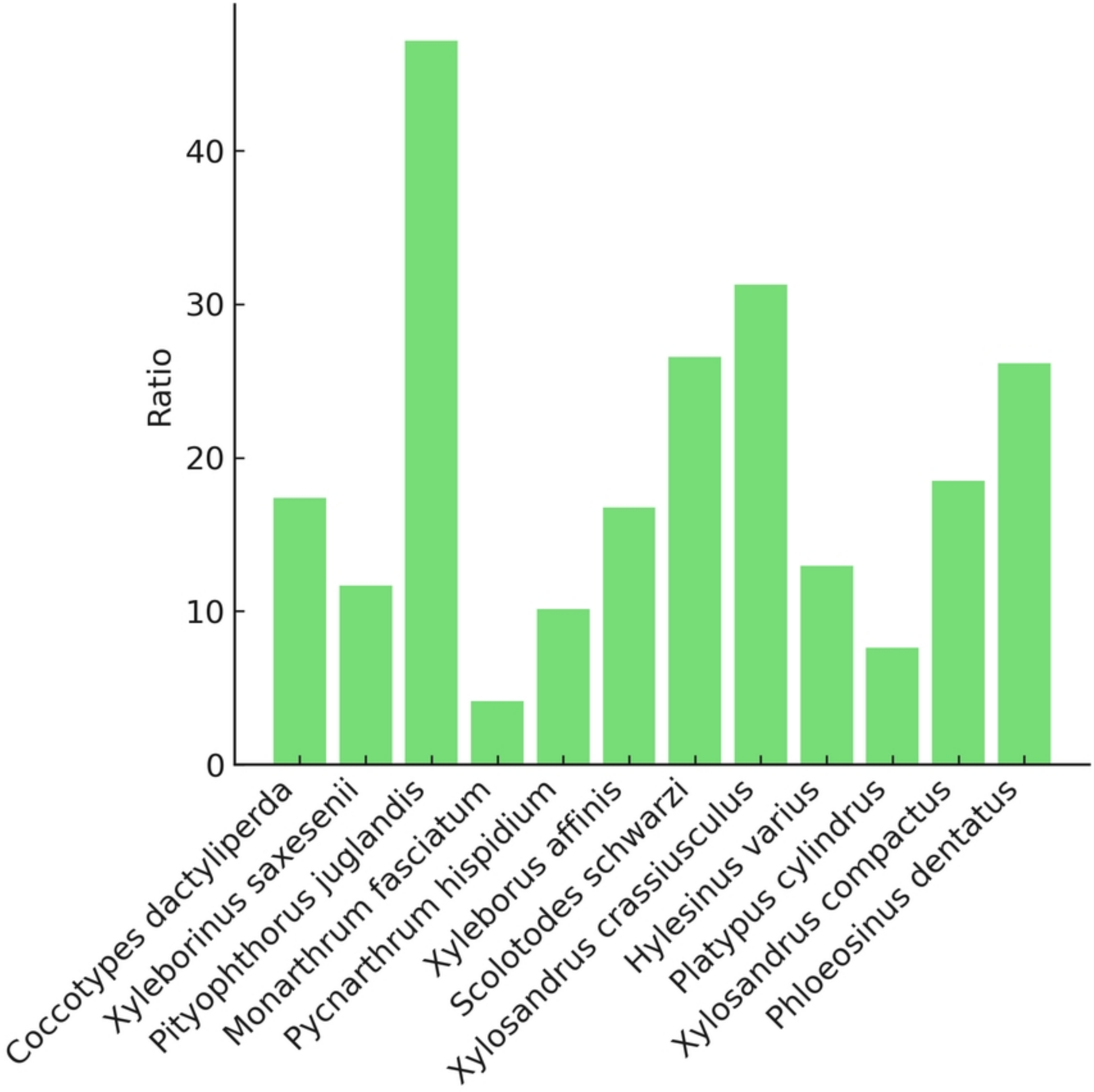
46. Kumar P, Rawat P, Chauhan S. Contrastive self-supervised learning: review, progress, challenges and future research directions. Int J Multimed Inf Retr [Internet]. 2022 Dec 1 [cited 2023 Jun 27];11(4):461–88. Available from: https://link.springer.com/article/10.1007/s13735-022-00245-6

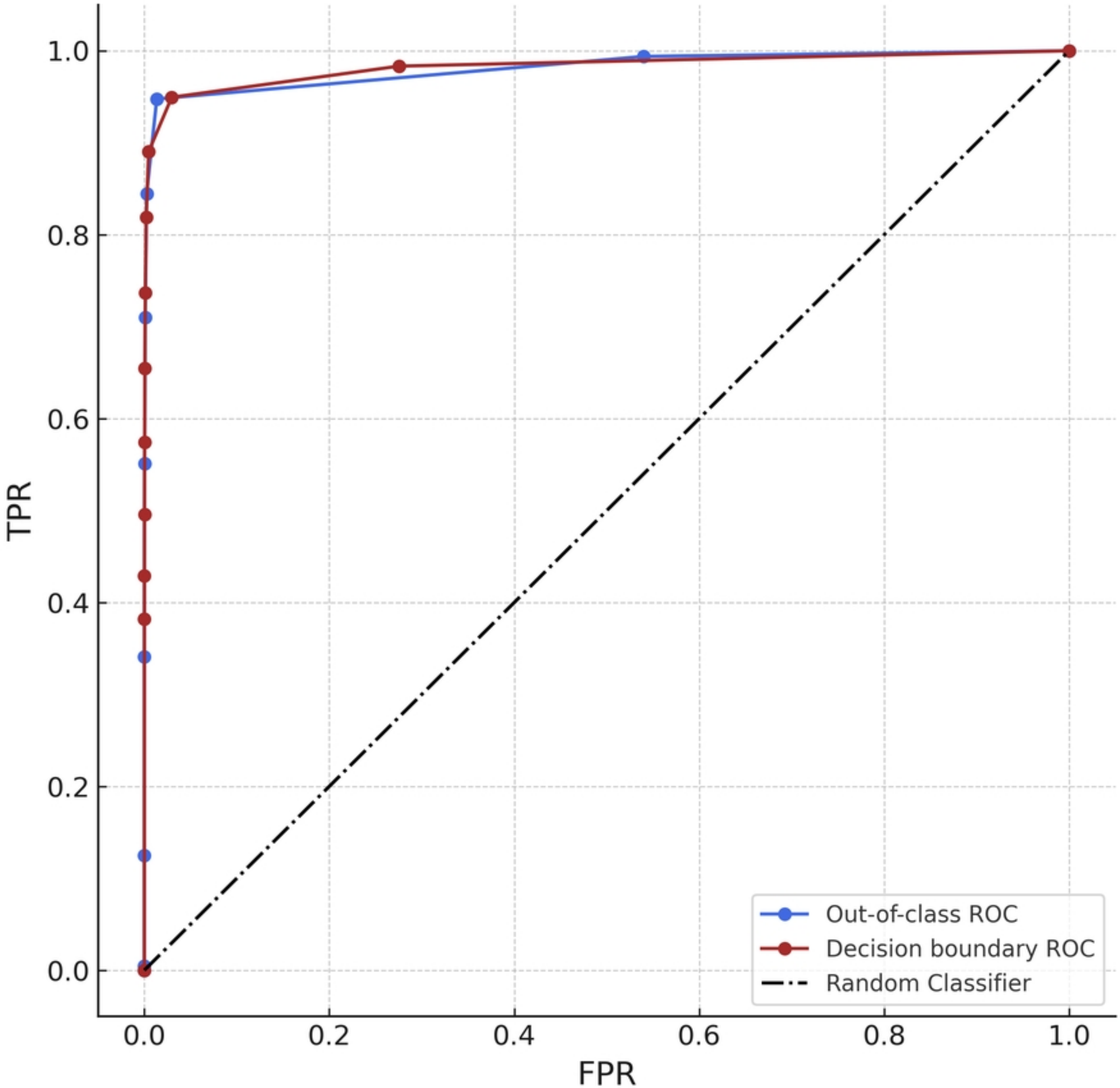
Train
Test
Train Train Train Train Validation Test
Train Train Train Validation Train Test
Train Train Validation Train Train Test
Train Validation Train Train Train Test
Validation Train Train Train Train Test

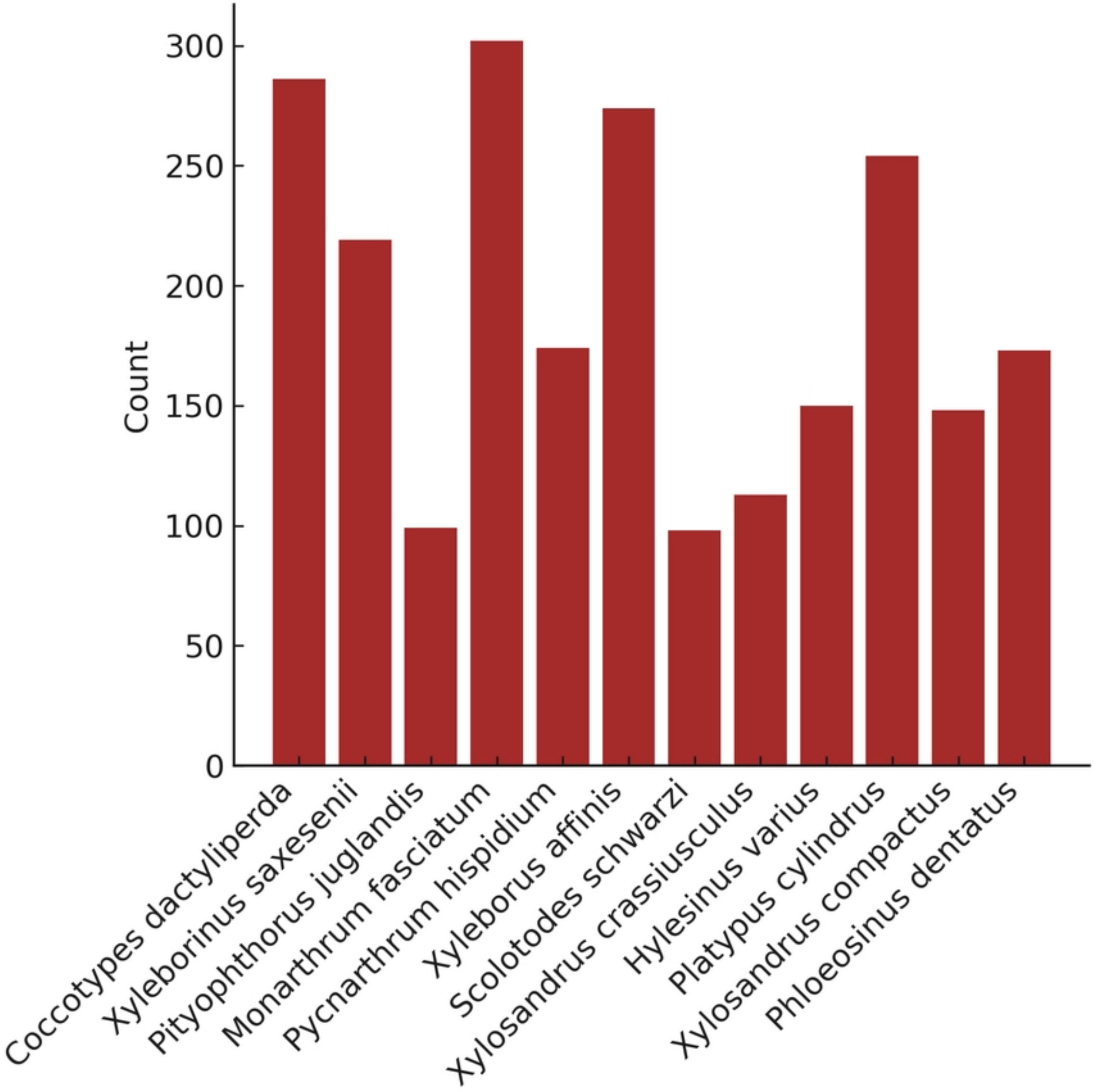



Training and Validation Loss over Epochs
Training Loss
Validation Loss
Loss
Epoch
5
4
3
2
1
0
1
2
3
4
5
6


Count
5000
4000
3000
2000
1000
0
Coccotypes dactyliperda
Xyleborinus saxesenii
Pityophthorus juglandis
Monarthrum fasciatum
Pycnarthrum hispidium
Xyleborus affinis
Scolotodes schwarzi
Xylosandrus crassiusculus
Hylesinus varius
Platypus cylindrus
Xylosandrus compactus
Phloeosinus dentatus


Ratio
0
10
20
30
40
Coccotypes dactyliperda
Xyleborinus saxesenii
Pityophthorus juglandis
Monarthrum fasciatum
Monarthrum hispidium
Pycnarthrum
Xyleborus affinis
Scolotodes schwarzi
Xylosandrus crassiusculus
Hylesinus varius
Platypus cylindrus
Xylosandrus compactus
Phloeosinus dentatus


1.0
0.8
0.6
0.4
0.2
0.0
TPR
0.0
0.2
0.4
0.6
0.8
1.0
FPR
Out-of-class ROC
Decision boundary ROC
Random Classifier


Count
300
250
200
150
100
50
0
Coccotypes dactyliperda
Xyleborinus saxesenii
Pityophthorus juglandis
Monarthrum fasciatum
Monarthrum hispidium
Pycnarthrum
Xyleborus affinis
Scolotodes schwarzi
Xylosandrus crassiusculus
Hylesinus varius
Platypus cylindrus
Xylosandrus compactus
Phloeosinus dentatus