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Early Detection and Segmentation of Bark Beetles Using *ResNet*50

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Abstract. Climate change poses a significant threat to global ecosystems, leading to an increased proliferation of pests in both agricultural and forested regions. In Mexico, this phenomenon has facilitated the spread of the bark beetle (as *Dendroctonus*) to higher altitudes, a challenge that traditional manual monitoring methods cannot effectively address. Currently, forest rangers manually count beetles in traps, a time-consuming process that often leads to delayed action of the corresponding authorities and thus, the burning of infested areas as the only viable solution in accordance with the Mexican Official Standard *NOM-019-SEMARNAT-2017*. This work proposes an automated early detection and classification system for bark beetles to streamline the monitoring process. The system leverages Connected-Component Labeling for the precise detection and counting of insects. For classification, a modified *ResNet*50 residual neural network is utilized, but with a modification to the custom layer. Our approach achieves a high performance, with an accuracy exceeding 90% on a dataset augmented with over $3,000$ images. The system successfully classifies two key species, *Dendroctonus mexicanus* and *Dendroctonus frontalis*, demonstrating its potential to significantly improve pest management efficiency and reduce the need for drastic measures like prescribed burns. This automated solution offers a timely and effective alternative to traditional methods, enabling a more proactive and targeted response to forest infestations.

Keywords. Convolutional neural network, *ResNet*50, segmentation, classification, bark beetles.

1 Introduction

Mexico has a little more than 66 million hectares of tropical and temperate forest ecosystems; this latter corresponds to 20% of the national territory [2, 7]. The bark beetles of the genus Dendroctonus are among the most significant pests in temperate forests worldwide. Mexico, with its extensive coniferous forests, and being the pine forests 75% of these, presents several types of risk of infestation in all states located throughout the Sierra Madre Oriental and Occidental, as well as the Trans-Mexican Volcanic Belt [8]. The National Forestry Commission (CONAFOR) shares the status of the situation monthly via the Bark Removing Insects Report [8]. An interesting fact presented in this report is the impact and effects caused by climate change, which have had severe consequences since 2013, directly impacting 12% of pine forests in Mexico, presenting infestations caused by several varieties of Dendroctonus [8] which have increased their presence at altitudes where they could not previously proliferate. Unfortunately, in any case, following the Mexican Official Norm *NOM-019-SEMARNAT-2017* [36], the solution was to destroy the infected forests.

On the other hand, the predominant process for acquiring and processing information related to pest control in forests is realized manually. First, the forest ranger periodically checks the traps

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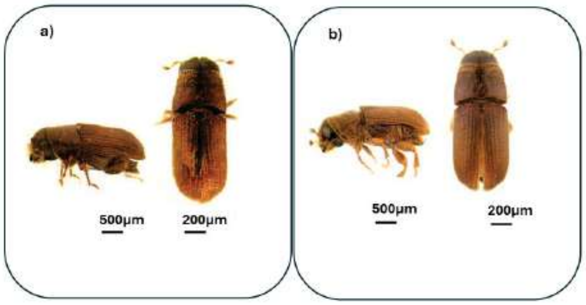

Fig. 1. Several features characterized by [1] a) *Dendroctonus mexicanus* is present throughout the country at altitudes above 2000 meters; average size is 3.5 mm, and its coloration is black in the head and body with a dark brown to black color. b) *Dendroctonus frontalis* is present throughout the country at altitudes above 1500; average size is 2.5 mm, and its coloration is in several shades of brown

called Lindgren funnel traps [30] placed in the trees. A principal function is the physical count of insects contained in these, as an early recognition of a growing population of bark beetles. Following the *NOM-019-SEMARNAT-2017* [36] information obtained must be sent to the relevant authorities for identification and analysis. However, the delay from capture to official recognition and declaration of a plague or infestation is a critical problem due to the time required to send and receive the information. Moreover, other relevant elements that consider the problem as a plague imply that factors such as the presence of natural predators [24] and environmental conditions [23] must be thoroughly considered to determine the appropriate response to possible infestation. Therefore, the problem becomes a question of acting in time.

The present proposal involves a scheme to develop an automated process for detecting, segmenting, and counting bark beetles of two different species *D. mexicanus* and *D. frontalis* (see Fig. 1). This technique consists of a *segmentation* and *classification* process. Hence, using Digital Image Processing (DIP) allows us to establish a baseline that corresponds to the segmentation and counting process of bark beetles. Based on this information, the automation process is generated using, in principle, Convolutional Neural Networks (CNN). However, it is introduced to address the degradation problem by considering a deep residual learning framework, such as *ResNet*50. Outcomes will be evaluated and fine-tuned to achieve optimal performance in order to consider the classification of two morphologically similar species. This will provide a preliminary and quick overview of the characterization of these types of pests.

2 Related Work

In Mexico and other countries, the Lindgren funnel traps are implemented as a preventive mechanism. This popular method for capturing bark beetles is achieved manually through traps and semiochemicals. This consists of a series of vertically arranged black funnels that mimic the vertical appearance of a trunk tree, and a collecting vessel at the base where insects are trapped as explained in [15] and [30]. Through the use of semiochemical pheromones [32]; by means of synthesizing these pheromones targeted specifically for bark beetles, these work as bait inside the traps through which they are later identified [18].

Accordingly, it is not expected that capturing different species of insects falling into this trap, since the semiochemical bait is targeted at bark beetles. However, the counting and separating of varieties of the same species continues to be a challenge.

Some proposals to address this topic are founded on advanced computer vision techniques to perform segmentation and classification of captured insects [13, 17, 24]; thus, several proposals have been suggested to accurately identify bark beetles, as presented in [9, 17].

In the Mexican context, the implementation of machine learning and deep learning techniques for detecting harmful organisms has primarily focused on agricultural systems [13, 10, 27, 4], with data acquisition of multispectral imagery predominantly carried out through unmanned aerial vehicles (UAVs) [20, 6]. According to annual state-level reports issued by the CONAFOR through the Comprehensive Forest Phytosanitary Surveillance

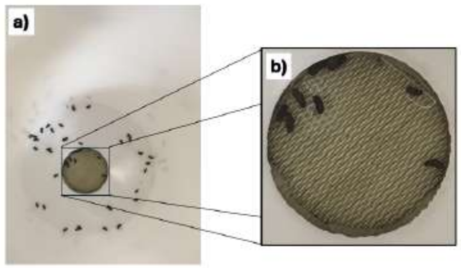

Fig. 2. a) Heterogeneous distribution of bark beetles in the raw image size of 4032×3042 pixels; the full length of a Dendroctonus *[frontalis, mexicanous]* is close to $[2.5, 3.5]$ mm [1], respectively; in this case, considering a scale of approx. 6 pixels to 1 mm; b) zoomed-in image highlights the aggregated difficulty of having more than one background, each with different textures

and Control System (SIVICOFF), since 2020, georeferenced digital aerial mapping has been incorporated for the early detection of infestation hotspots [29], with greater technological adoption among private owners of forest areas. In states such as Durango and Chihuahua, the use of Recurrent Neural Networks (RNNs) has enabled the preliminary development of spatial prediction models to identify areas with a high probability of outbreaks [29]. Nevertheless, there remains an absence of an integrated automated system capable of detecting the first symptoms of infestation through the analysis of satellite or UAV imagery, given that the UAV imagery processing is realized when the problem already exists and is in an advanced state and only remains, hence to actuate according to the *NOM-019-SEMARNAT-2017* [36]. Therefore, the initial detection of pest forest relies on in situ recognition conducted by forest technicians, who can constitute the first link in the early warning chain.

3 Methodology

Figure 3 presents a schematic diagram corresponding to the proposed solution. A *segmentation* using Digital Image Processing to characterize the original dataset, as well a *classification* pipeline designed to provide a preliminary assessment of the captured images, concerning significant beetle counts in accordance the different species contained in the traps; which are classified in accordance to the type specie, in this case Dendroctonus *mexicanus* and *frontalis*.

On the other hand, it is important to note that, in the image acquisition process (out of scope of this paper), slight variations in illumination factors or different parameters resulting in acquired images, for example, realizing a physical zoom with the vision system, can thus distort the size of the insects. These variations complicate consistent detection across the database.

3.1 Segmentation Process

The *segmentation process*, which extracts the insects from the whole image, corresponds to an image processing phase (see Fig. 3*a-d*). The efficacy of this stage relies on basic morphological filters to obtain a clean image, as well as Boolean Map-Based Saliency [37]. Different limitations are presented, including the expected image environment inside the Lindgren trap as illustrated in Fig. 2, where the distribution of bark beetles is not uniform, nor is the background. Nevertheless, the acquisition process, even if significantly important, is not determinant for the training models [25].

Therefore, the process involves testing some representative methods, such as *Sliding Window* [31] or *Connected-Component Labeling (CCL)* [14] techniques. A factor to consider in the Sliding Window technique is that insect sizes are relatively uniform, but, in reality, this is not necessarily true. For that reason, it is assumed that an average window size 100×100 pixels. Hence, the first step is to obtain features to separate the species trapped, which can be modified per the existing relation with work distance, if the vision system is not fixed. Thus, based on the initial results obtained [19], the CCL technique was chosen.

Cruz and Ayala present in [3] CCL as a strong strategy to separate information $3D$ based on a typical CCL technique; under this concept, our proposal, which used the Connected-Component Labeling method was carried out by identifying

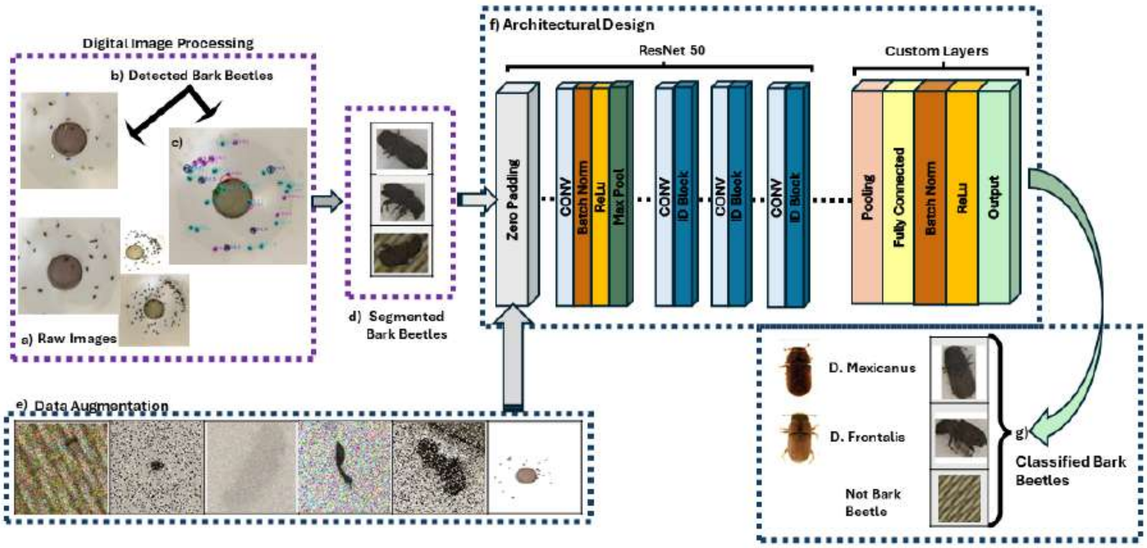

Fig. 3. Schematic description to classify two types of Bark Beetles: *D. Mexicanus* and *D. Frontalis* accordance to [1]. **Segmentation Process** previous propose in [19] involved a) characterization of the Dataset, which was realized with DIP technique; b) to d) present the detected and segmented Bark Beetles. **Classification Process** starting with a e) data augmentation conforming to individual insects and processing information through f) proposal architectural design to finally, g) classification of bark beetles

groups of adjacent foreground pixels. These connected components ideally hold the coordinates to segment each insect individually, allowing for subsequent classification of these. Consequently, we still had to address the varying distance between the insects and the vision device. The segments are labeled with different colors based on their area (see Fig. 3*b-c*).

3.2 Classification Process

General structure corresponding to *classification process* can be seen in Fig. 3*f*. Starting from the original dataset to get a new dataset conforming to the individual insects, to performing data augmentation to train the proposed model (see Fig. 3*e*). In accordance with Martínez *et al*. [19], the model's ability to handle noisy data and simulate varying conditions of lighting, texture, and distortion using common noise filters.

On the other hand, in principle, the selection of the Convolutional Neural Network architecture was inspired by *VGGNet* [21]. CNNs leverage this data format to extract the maximum number of features from each image in the dataset. A principal advantage of the CNN is the preservation of spatial information as well as the background work supporting it [5, 33]. Then, if the core information in an image is the value of each pixel per color channel, it is the spatial arrangement of these pixels. In this sense, similar proposal can be founded in the proposals [16, 28]. CNNs leverage this data format to extract the maximum number of features from each image in the dataset. While a CNN was the first suggestion for our proposal, it was also tested for classification through various linear models, including K-Nearest

Neighbors (KNN), Naïve Bayes (NB), and Kernel Support Vector Machines (SVM).

3.2.1 *ResNet*50

As mentioned above, the selection of the CNN architecture concerning to this proposal was inspired by [21]. It consists of a series of small 3×3 convolutional layers, each one followed by a max-pooling layer, finishing in a fully connected layer. Given the dataset's singular level of complexity, the architecture initially consisted of only three convolutional layers. Finally, we considered that, *ResNet*50 is a specific architecture with a structure similar to a generic CNN, but strategically organized with residual blocks and skip connections.

Due to the sigmoid nature of classification and the dataset's more than $3,000$ images from both classes, the architecture shown in Fig. 3*e* is sufficient for significant performance. This was chosen as the main classification strategy to present, given that other solutions, such as pre-trained models, are overly complex for simple tasks, e.g., distinguishing insects from noise or several changes in the illumination, or confusion with the texture. Their deep attributes may capture irrelevant patterns, leading to poor generalization. In this sense, to select a variation of the CNN as an architecture more specific *ResNet*50 as the base model to leverage transfer learning (see Fig. 3*b-c*). It is argued in [26] that the performance can be achieved with employment-pretrained models, which have been focused on large datasets and can be adapted to specific tasks via transfer learning techniques. *ResNet*50 was selected from a broad variety of base models due to its residual connections, which help train networks by mitigating issues like gradient vanishing.

The base model custom layers were added to be trained on the dataset specific to this proposal solution. These include a flattened layer, a dense layer with ReLU activation, and a dropout layer is performed to reduce overfitting risk (see Fig. 3*e* Custom Layers). Initially, all pretrained model layers remain inactive, so only the custom layers are trained. Later, in a second fine-tuning phase, the last layers of the base architecture are active, allowing their weights to be adjusted to fit the current training without compromising previously learned knowledge. In this last phase, a reduced learning rate of 1×10^{-5} prevents abrupt changes in optimized weights.

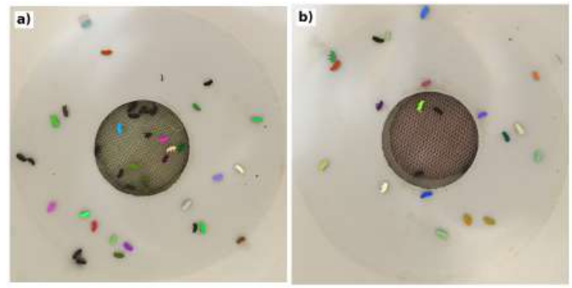

Fig. 4. Segmented insects highlighted by colors; note that the center background (from the trap) presents problems in separating the bark beetles, due to the coloration and texture of this

A fundamental metric considered for the segmentation is the accuracy. This supports the evaluation of the average ratio between the detected number of insects in the image and the actual number of insects. The *Intersection over Union* ($\mathbf{IoU} = \frac{A \bigcup B}{A \bigcap B}$) metric, which compares the overlap between the automatic segmentation and a manually generated reference segmentation, as specified in similar proposals presented in [12, 34]. Therefore, this metric provides consistent information on the evaluation of the system's performance, in terms of an accurate detection and the minimization of false positives and negatives as presented by [22] and [35].

4 Results and Discussion

Raw database was acquired in a semi-controlled laboratory environment that emulates a Lindgren funnel trap similar to the methodology proposed by Sun *et al.* in [33], with a singular difference being relatively clean traps (see Figs. 2 and 4). Despite the detected process presenting a loss of information corresponding to the center of the tramp(see Figs. 2 and 4), the total detected beetles was considered. This is because we established that the number of insects detected per area is

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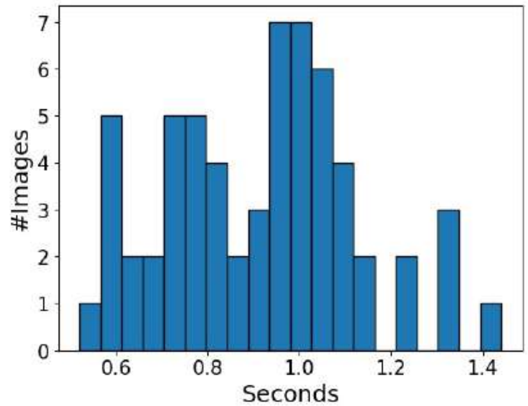

Fig. 5. Segmentation process times per image

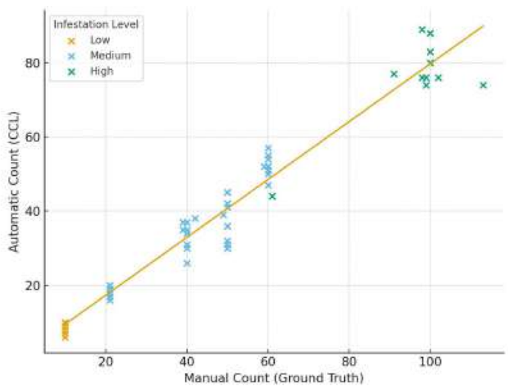

Fig. 6. Obtained results to over time, approximately one month. The maximum count of Bark Beetles was near 120 (both, *D. mexicanus* and *D. frontalis*, Ground truth) were counted during the *segmented process* using CCL technique. This count allow us establishment a categorization of possible infestation levels

greater than the number not detected. However, to have the best results, it is necessary to perform an analysis of the texture of the center background of the trap. On the other hand, the training dataset used in this proposition consisted of a total of $3,276$ synthetic images generated following the previous proposal presented by Martínez *et al.* in [19]. These images and code for the previously explained solution are available at [11].

The IoU-based evaluation reveals that while spatial segmentation quality (IoU and Precision) remains limited due to complex trap textures and uneven illumination, the quantitative detection performance (Recall and Count Accuracy) is strong. This confirms that the CCL-based segmentation method provides reliable beetle enumeration, even though improvements are needed in object boundary localization.

According to the obtained results of the *segmented process* highlight Connect-Component Label as the technique is more effective to realize this process. A sample of the times per image realized during the *segmentation process* is illustrated in Fig. 5. To prove the computational efficiency of CCL compared to other models (e.g. Slide Windows), with an average of approximately one second per image, the performance of CCL was additionally evaluated using the **IoU** metric described earlier, through which other relevant metrics such as accuracy, precision, and recall are derived, whose average values are summarized in Table 1; which presents a brief of each metrics.

The segmentation stage achieved an **IoU** of 28.69%, a precision of 33.79%, and a recall of 69.76%, indicating that although the system succeeds in detecting most beetles (high recall), it still struggles with the precise delineation of insect contours and tends to produce false positives in textured regions. Counting accuracy reached 92.5%, based on manual validation, confirming that the system provides reliable estimates of beetle population despite segmentation inconsistencies. Additionally, in Fig. 6, a simple segmentation is found to consider several infestation levels.

A lack of balance is referred to as residual noise remaining after preprocessing. Despite the performance of features as ratio, saturation, and shape of detected objects in the resultant components after preprocessing, it helps to discard the remaining components that do not specifically target the beetles.

The quantification of both species of bark beetles in the raw data can be shown through Fig. 6. Hence, CCL demonstrated good performance with an accuracy of 0.925 over the expected bark beetles to count per image. Figure 6 as an example of the result of detected bark beetles in more 60 images corresponds to the original dataset. As shown, the maximum count ascends close to 120

Table 1. IoU-based metrics for segmentation using the Connected-Component Labeling (CCL) technique

Metric	**Symbol / Formula**	**Reported Value**	**Description (Application Context)**
Intersection over Union (IoU)	$\mathrm{IoU} = \frac{\lvert A\cap B\rvert}{\lvert A\cup B\rvert}$	28.69%	Measures the overlap between the predicted (automatic) segmentation and the manually labeled ground truth. A value below 30% indicates limited spatial agreement, often caused by texture noise or partial detection.
Precision	$\frac{TP}{TP+FP}$	33.79%	Indicates the proportion of predicted beetles regions that are correctly segmented. Low precision suggests confusion between the background texture and the beetle regions (e. g., at the center of the trap).
Recall (Sensitivity)	$\frac{TP}{TP+FN}$	69.76%	Represents the fraction of real insects successfully segmented. Higher recall implies most beetles are detected, though not necessarily well-localized.
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	97.86%	Reflects global classification correctness, though biased by the large non-insect background area. It should be interpreted with caution in segmentation tasks with strong class imbalance.
Count Accuracy	$1 - \frac{\lvert N_{auto}-N_{manual}\rvert}{N_{manual}}$	92.5%	Quantifies how closely the automatic counting matches the manual count. Despite low IoU, high count accuracy shows that most insects are detected even if boundaries are imprecise.

Table 2. Classification Metrics of the VGGNet-like Base Model

	Precision	Recall	F1-Score	Support
Not a Beetle	0.97	0.92	0.96	156
D. frontalis	0.98	1.00	0.99	277
D. mexicanus	0.90	0.96	0.97	225
Accuracy	-	-	0.99	655
Macro Avg	0.99	0.95	0.96	655
Weighted Avg	0.99	0.99	0.99	655

Table 3. Classification Metrics of the *ResNet*50 Model

	Precision	Recall	F1-Score	Support
Not a Beetle	0.97	0.98	0.99	171
D. frontalis	0.99	1.00	0.99	232
D. mexicanus	0.96	0.96	0.99	230
Accuracy	-	-	0.99	655
Macro Avg	0.97	0.98	0.99	655
Weighted Avg	0.99	0.99	0.99	655

bark beetles, which points to several problems of infestation.

On the other hand, using 655 images corresponding to data augmenting with respect to *classification process*, using a classical CNN obtained an excellent accuracy, as shown in Table 2. However, *ResNet*50 slightly outperformed, as presented in Table 3. In both cases, their confusion matrix is presented Fig. 7. As observed in Fig. 7a) and 7b) available first, the confusion matrix corresponds to detecting or not only Bark Beetles. While Fig. 7c) and 7d) support the

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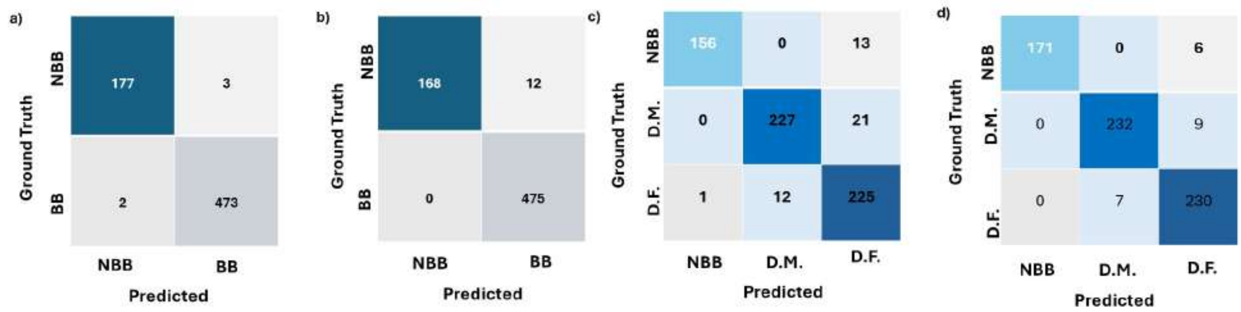

Fig. 7. Confusion Matrix corresponds in first instance, to classify as Bark Beetle (BB) and Non-Bark Beetle (NBB) for a) classical CNN and b) *ResNet*50. The images c) and d) categorizing NBB, Dendroctonus frontalis (D.F.) and Dendroctonus mexicanus (D.M.) for classical CNN and *ResNet*50, respectively

evaluation of performance related to *ResNet*50 pointed to classify the species *D. frontalis* and *D. mexicanus*. To ensure accurate performance, the chosen optimizer was *AdamW* with *cosine decay* and an introductory rate 1×10^{-3} to improve generalization and prevent large gradient updates, both contributing to avoid overfitting.

However, it is noteworthy that the other models also performed remarkably well, as shown in Fig. 8. This outcome is understandable given the current dataset. We expect the performance to change as we incorporate more insect species and introduce greater complexity to the setup. Moreover, the presented accuracy can be partly attributed to the inclusion of the resulting images, obtained by applying the various noise filters discussed in [19], as part of the training set.

To note that, during the training phase, several potential biases may influence the model's performance and generalization capability. First, *dataset bias* arises from the predominance of synthetic or semi-controlled images, which may not accurately reflect the lighting variability, background textures, or insect occlusions present in real forest environments. This can lead to overfitting to laboratory conditions and reduced robustness in field applications. *Class imbalance* between *D. frontalis* and *D. mexicanus*, and non-beetle instances may also distort decision boundaries, favoring the majority class. Furthermore, *annotation bias* can occur if manual labeling inconsistencies propagate through the augmentation process, amplifying systematic errors. Lastly, *sampling bias* may emerge from the limited number of trap configurations used during image acquisition, restricting the representativeness of the training data.

5 Conclusion and Future Work

In state-of-the-art insect detection, the segmentation process typically involves tuned and complex models that employ heuristic techniques or challenging segmentation models to select the beetles in crowded environments. Nevertheless, our approach demonstrates that introducing CCL after proper preprocessing has yielded significant results.

Currently, we can confidently affirm that our segmentation model is effective as long as the insects in the image have sufficient contrast with their background, and this is because the traps were previously cleaned. However, despite this, a challenge to improve corresponds to the processing of the central part corresponds to traps that need an extra processing to improve performance due to the abrupt change in texture in this region. To mitigate these issues, future work should incorporate cross-domain datasets, stratified sampling, and normalization strategies that enhance ecological and visual diversity.

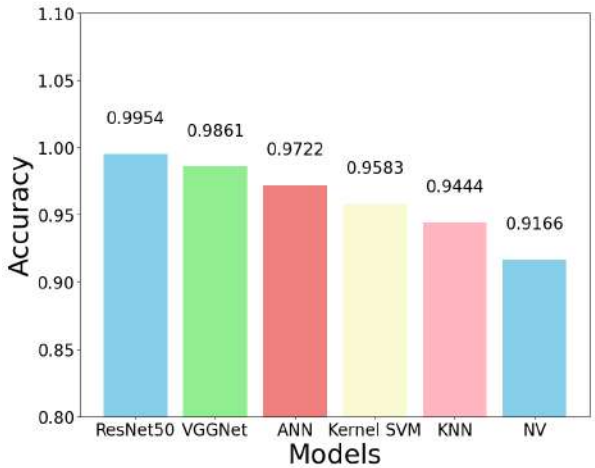

Fig. 8. Accuracy classification model

Moreover, to addition of texture features the classification process is expected to increase its difficult, therefore, it is important to evaluate the performance of the other models additionally to *ResNet*50 or classical CNN may decrease its performance according the classification task becomes more complex, e.g., original images obtained using a Lindgren funnel trap in the forest, even though the improvement custom layer a principal function is strengthen the performance of the proposed architecture. Finally, the objective is to develop an application or app to allow the forest ranger an early detect and classify the different species of bark beetles early to prevent the infested forest zone and, thus, the destruction of this.

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