# Segmentation of plywood veneers as a pre-processing step in image analysis for material quality assessment

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***Abstract.*** *The aesthetic quality of wood veneers is a decisive factor in adding value to the industry. Manual inspection presents limitations such as subjectivity and fatigue, motivating the use of Computer Vision. This study presents an approach to segment the veneer region in images collected in a real environment, aiming to adequately identify the area of interest for subsequent material quality classification. A YOLOv8 model trained for this purpose achieved a mAP@50 of 0.995 on the experimental database composed of 106 annotated images. Additionally, the model was qualitatively evaluated on 1,000 unlabeled images acquired under real operating conditions, yielding consistent, visually coherent segmentation results.*

## 1. Introduction

In addition to the solid wood industry, the plywood industry is fundamental to the forestry sector and contributes significantly to the economy. Manufacturers produce plywood by joining multiple layers of wood veneers. Plywood panels offer aesthetic appeal, low weight, high strength, dimensional stability, acoustic insulation, and low thermal conductivity [Ramos-Maldonado et al. 2025]. These veneers are valued for their aesthetic appeal; therefore, evaluating this characteristic is essential to properly differentiate high-quality panels used in exterior applications from lower-quality panels used for other purposes, ensuring greater added value for companies in this sector.

In this context, quality analysis of solid and laminated wood is a step adopted by most factories in this segment. Defect inspection is important for improving wood quality and minimizing resource waste. However, manual inspection is subject to subjectivity and inherent limitations, such as fatigue and decreased attention span. Computer Vision-based methods have revolutionized defect inspection in wood, overcoming human limitations and providing greater accuracy and efficiency, with wide application [Yi et al. 2024].

Even with automated methods for wood inspection already proposed [Yi et al. 2024], some challenges persist, including variations in the size, shape, and texture of the wood surface, as well as environmental factors such as lighting conditions. In recent work, methods based on Computer Vision, particularly Convolutional Neural Networks (CNNs), have gained prominence in wood inspection, having been successfully applied to wood type/species classification [Nguyen-Trong 2023] and defect identification [Wang et al. 2024, Hoang et al. 2025].

These methods are commonly used to classify types of wood defects. However, we intend to develop a new approach to classify wood laminates that accounts for different quality levels. To this end, we are carrying out the project in partnership with a wood laminate company in southwestern Paraná, which is providing real images and supporting its labeling for the construction of the experimental database.

To achieve this objective, we applied a pre-processing step to identify the region corresponding to the laminate. We constructed an experimental database containing 106 annotated images, which we used to train and evaluate a YOLOv8 model configured for laminate segmentation. The model achieved a Mean Average Precision (mAP@50) close to 100%, demonstrating high segmentation accuracy and strong generalization capability. To further assess the model's robustness in real-world conditions, we also performed a qualitative evaluation using 1,000 additional unlabeled images collected in an industrial environment.

## 2. Theoretical Foundation

Semantic segmentation is a Computer Vision task that assigns a class label to each pixel in an image, producing a dense, structured representation of the scene. Semantic segmentation is based on Convolutional Neural Networks (CNNs) [Long et al. 2015]. Later models incorporated encoder-decoder type architectures, such as the U-Net [Ronneberger et al. 2015].

In this scenario, models from the YOLO (You Only Look Once) family, initially proposed for real-time object detection [Redmon et al. 2016], have begun to incorporate segmentation extensions, most recently adding specific heads for mask prediction [Sapkota and Karkee 2025]. Although YOLO is traditionally associated with instance detection and segmentation, its adaptations demonstrate that single-stage architectures can perform segmentation with high computational efficiency, making them attractive for applications that demand real-time processing.

One of YOLO's main advantages for segmentation is its ability to operate in real time, maintaining high accuracy even in scenarios with multiple objects and varying lighting conditions. Furthermore, its modular architecture facilitates training with customized databases, a feature relevant to specific applications such as segmenting wood veneers in industrial environments [Kang and Kim 2023].

## 3. Methodology

The experimental dataset, composed of 106 images of Pinus elliottii leaf blades, was labeled on the Roboflow platform (https://roboflow.com/) and divided into 69 for training, 20 for validation, and 15 for testing. Data augmentation with horizontal mirroring was applied to the training set, resulting in 207 images used for learning.

The annotated dataset was exported in a format compatible with YOLOv8 Instance Segmentation, allowing for reproducible training. The model was trained on Google Colab using the Ultralytics YOLOv8 framework, initialized from pre-trained weights (yolov8n-seg.pt) and subsequently fine-tuned with the annotated dataset. During training, all images were resized to 640×640 pixels to match the YOLO model's input size.

We monitored model performance using loss curves and standard segmentation metrics (precision, recall, mAP@50, and mAP@50–95). Precision measures the proportion of correctly predicted segmented regions among all predicted regions, reflecting how accurate the model's optimistic predictions are. Recall evaluates the proportion of correctly detected regions relative to all ground-truth regions, indicating the model's ability to identify relevant objects. The mAP@50 metric computes the mean Average Precision at an Intersection over Union (IoU) threshold of 0.50, while mAP@50–95 averages performance across multiple IoU thresholds (0.50-0.95), providing a more comprehensive assessment of segmentation quality.

## 4. Results

Table 1 presents the quantitative results with the trained model applied to the test set. Figure 1 shows an image of a laminate from the test set, and the result of segmenting the object of interest in red, in which small seeding flaws can be observed in the lower part of the image.

**Table 1. Results of the segmentation model applied to the test set**

| Metric | Value |
|---|---|
| Precision | 1.0000 |
| Recall | 0.9985 |
| mAP@50 | 0.9950 |
| mAP@50-95 | 0.9755 |

**Figure 1. Example of a segmented objects**

The model demonstrated consistently high performance across all evaluated metrics. The elevated precision and recall values indicate accurate identification of laminate regions, with minimal false positives and false negatives. Likewise, the strong mAP@50 and mAP@50–95 scores confirm the robustness and spatial consistency of the segmentation results across different IoU thresholds. These findings validate the effectiveness of the proposed pre-processing stage and provide a solid foundation for the subsequent phase of the project, which focuses on material quality classification based on the segmented regions.

Furthermore, we performed a qualitative assessment by applying the trained model to 1,000 laminate images without ground-truth annotations. In all cases, the segmentation outputs were visually coherent and aligned with expected laminate boundaries, reinforcing the model's generalization capability in real-world scenarios.

## 5. Conclusion

The results indicate that the YOLO-based approach is practical for segmenting the region of interest, reducing background interference, and providing a reliable basis for subsequent quality analysis. Qualitative and quantitative analyses demonstrated that the model correctly identifies the veneer, reinforcing its viability as a pre-processing step in automated inspection systems.

We are expanding the experimental database and plan to use it as the foundation for proposing a complete pipeline for veneer classification in a real-world environment. We also intend to make the expanded database publicly available. In future studies, we will explore integrating the proposed segmentation step with methods for detecting and classifying various wood veneer defects, such as live knots, dead knots, insect holes, cracks, and bark.

## References


Hoang, V. T., Le, V.-T., Dinh, N., Tran-Trung, K., Van, B. N., Hong, H. D. T., and Huong, T. H. (2025). Deep Learning-based faulty wood detection with area attention. *Computers, Materials & Continua*, 85(1).

Kang, C. H. and Kim, S. Y. (2023). Real-time object detection and segmentation technology: an analysis of the yolo algorithm. *JMST Advances*, 5(2):69–76.

Long, J., Shelhamer, E., and Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3431–3440.

Nguyen-Trong, K. (2023). Evaluation of wood species identification using CNN-based networks at different magnification levels. *International Journal of Advanced Computer Science and Applications*, 14(4).

Ramos-Maldonado, M., Gutiérrez, F., Gallardo-Venegas, R., Bustos-Avila, C., Contreras, E., and Lagos, L. (2025). Machine learning and industrial data for veneer quality optimization in plywood manufacturing. *Processes*, 13(4):1229.

Redmon, J., Divvala, S., Girshick, R., and Farhadi, A. (2016). You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 779–788.

Ronneberger, O., Fischer, P., and Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer.

Sapkota, R. and Karkee, M. (2025). Ultralytics yolo evolution: An overview of yolo26, yolo11, yolov8 and yolov5 object detectors for computer vision and pattern recognition. *arXiv preprint arXiv:2510.09653*.

Wang, R., Chen, Y., Liang, F., Wang, B., Mou, X., and Zhang, G. (2024). Bpn-yolo: a novel method for wood defect detection based on YOLOv7. *Forests*, 15(7):1096.

Yi, L. P., Akbar, M. F., Ab Wahab, M. N., Rosdi, B. A., Fauthan, M. A., and Shrifan, N. H. (2024). The prospect of Artificial Intelligence-based wood surface inspection: A review. *IEEE Access*, 12:84706–84725.