# REAL-TIME KNOT DETECTION IN WOODEN MATERIALS USING OPTIMIZED YOLO ARCHITECTURE

Mihai BUTOLO [1], Anton HADAR [2,3,4,*], Nicolae GOGA [5,6], Florin BACIU [7], Ramona POPA [8], Alexandru BRATOSIN [9], Alexandru STANCIU [10], Miruna CIOLCA [11,*]

*Wood is still a basic and renewable material that is widely used today in modern industry, but its natural fluctuations and defects (knots) are a major challenge to quality grade wood. Knots disrupt grain structure, decrease mechanical performance and reduce visual uniformity of wood products therefore reliable inspections are essential for high quality wood products. Manual grading of wood has been time consuming and subjective with the largest limitation being human error which also restricts scalability as global wood demand continues to grow. Computer vision technology has provided effective solutions to real-time defect detection using deep-learning based object detection models such as YOLO. This study presents a deployable, modular framework for the automated detection of knots in wood products using YOLO. The focus is on the development of an industrial ready system, with industrial readiness being more important than just isolated accuracy gains. The proposed system combines preprocessing, inference, visualization and standardized data export and enables smooth interoperability with CAD/CAE, ERP and Digital Twin environments. The proposed system is tested with a carefully curated and validated dataset of beech wood. The system demonstrates flexibility across multiple industrial applications and supports scalable, reliable and sustainable wood processing.*

**Keywords**: Yolo AI, Knot Wood Detection, Imaging, Wood Processing

[1]* Corresponding authors: anton.hadar@upb.ro, miruna.ciolca@upb.ro,
PhD Student, Faculty of Industrial Engineering and Robotics, National University of Science and Technology POLITEHNICA Bucharest, Romania, e-mail: mihai.butolo@gmail.com
[2] Professor, Faculty of Industrial Engineering and Robotics, National University of Science and Technology POLITEHNICA Bucharest, Romania, e-mail: anton.hadar@upb.ro
[3] Technical Science Academy of Romania, Dacia Blvd. 26, 030167 Bucharest, Romania
[4] Academy of Romanian Scientists, Ilfov Street 3, 050045 Bucharest, Romania
[5] Professor, Faculty of Industrial Engineering in Foreign Languages, National University of Science and Technology POLITEHNICA Bucharest, Romania, e-mail: nicu.goga@upb.ro
[6] University of Groningen, the Netherlands; n.goga@rug.nl
[7] Assoc. Professor, Faculty of Industrial Engineering and Robotics, National University of Science and Technology POLITEHNICA Bucharest, Romania, e-mail: florin.baciu@upb.ro
[8] Lecturer, Faculty of Industrial Engineering in Foreign Languages, National University of Science and Technology POLITEHNICA Bucharest, Romania, e-mail: popa.ramona91@yahoo.com
[9] Lecturer, Faculty of Industrial Engineering in Foreign Languages, National University of Science and Technology POLITEHNICA Bucharest, Romania, e-mail: ioan.bratosin@gmail.com
[10] PhD Student, Faculty of Industrial Engineering and Robotics, National University of Science and Technology POLITEHNICA Bucharest, Romania, e-mail: stanciualexandru04@yahoo.com
[11] Lecturer, Department of Strength of Materials, Faculty of Industrial Engineering and Robotics, National University of Science and Technology POLITEHNICA Bucharest, Romania, e-mail: miruna.ciolca@upb.ro

## 1. Introduction

Recent advancements in computer vision revealed automatized solutions that address the above-mentioned challenges. Deep-learning-based object detection models, such as YOLO (You Only Look Once) offer speed and accuracy for real time defect detection, among other use cases [1]. By automating wood knots, identification can support modernization of wood fabrication industry and the global demand of wood [2].

Through the channels of object detection, You Only Look Once (YOLO) is remarkable as being suitable for the processing tasks immediately. The object detection frames such as YOLO permit simultaneous administration of the localization and classification, reaching a practical equilibrium between precision and speed [3, 4]. Several versions of this architecture – YOLOv3, YOLOv5 and the new YOLOv8 has been adopted on large scale in the tasks of industrial inspection where rapid inference truly matter [5, 6]. The speed is often not negotiable in these contexts.

Especially in wood processing, Cui et al. [7] has been shown that YOLO3 can detect successfully knots in pine frames, reporting clear improvements in recall, as general precision in comparison with traditional methods of computer vision, a significative step towards automated wood inspection. Based on this paper, J. Xu et al. [8] have improved YOLOv5 for detecting the flaws in wood and got reliable results in more categories than defects. Recent studies have explored architectural modifications, such as focalization modules and components based on transformation, to detect better the small or hidden defects. These improvements are extremely valuable for the knots that has irregular forms or reduced contrast – the type that usually confront with difficulties [9], [2].

A good example can be found in the plunks with limited computational infrastructure. Another practical issue is raised by the integration with the already existing software within an enterprise. Frequently, production installation depends on the ERP or MES systems, which require standardized results, machine readable, from inspection tools. Most academic prototypes do not even touch this aspect [10].

This study is meant to introduce a comprehensive frame, that can be implemented to automatically detect knots in wooden materials.

The main contribution of the authors in this paper is the use of a modular YOLO-based pipeline combining preprocessing, inference, annotation, visualization, and export modules. It runs on a local server as a single Python process – no containerization or distributed environment support needed.

## 2. Related work

The analysis operators for the texture, such as Gray Level Co-occurrence Matrix (GLCM) and Local Binary Models (LBP) were often used for describing the irregularities of the fiber, meanwhile the directional filters, such as Gabor and the wavelet transformations were used for detecting the changes of the orientation fibers [11, 12].

Guohau Lin [13] has proposed an easy and fully completely automation method for detection and knots association, based on machine learning. This method uses HDMI surface images for wooden boards, captured with industrial cameras and trained for a manual set of data. Almost 3000 images can be obtained from the initial dataset. These were first filtered for noise cancellation and split into two groups: images with visible knots and without knots. From each group, 573 images were selected randomly for building a balanced dataset. After this, they were split into training, validation and testing subsets, following a ratio of 7:2:1. Three variants of YOLOv8 (nano, medium and large) have been tested in this study. The performance was measured using standard metrics, including precision, recall, F1 score and medium precision (mAP), reaching this way a mAP of 0,0887 detection and a 0,85 precision for the task of knot association.

Beyond the approaches of deep learning, classical statistics classifiers such as Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) were applied to the visual characteristics that were manually created [14]. They were very efficient from the computational point of view, but their capacity to universalize different types of wood and types of defects was not very good.

**2.1. Transition to Deep Learning**

The introduction of deep learning has been transformed significantly in the way in which the defects of knots are detected and analyzed. The Convolutional Neural Networks (CNN) has eliminated the necessity of manual engineering of characteristics through visual hierarchical representation directly from raw image data. The earlier approaches based on CNN have been proved to be a better robust variation of illumination conditions compared to traditional techniques of computer vision.

Even though, many of these early models were limited to classification jobs, and by this it means that they could only determine if a flaw was present but were unable to precisely localize it on larger surfaces or wood panels [15].

Models based on YOLO are especially attractive for industrial environments, because they offer capabilities of real time interference and, at the same time, maintain a solid balance between the precision of detection and computational efficiency. Recent studies have significantly improved YOLO architecture by incorporating attention mechanisms of the networks based on transformation, optimization, quantity, and simplification, which allow the modules to run efficiently even on a hardware which has limited computational resources. For problems about detecting the defects of wooden boards, there were applied different frames of detection of the objects including Faster R-CNN [20] and EfficientDet [21].

### 2.2. Datasets and Annotation Practices

The convolutional neural networks (CNN) have eliminated the necessity of manual engineering of characteristics through visual model learning directly form the raw image. This is a major change. The first approaches based on CNN have proved a better sturdiness on illumination and noise changes than the traditional methods of computer vision. However, many of the earlier modules could not be made so much beyond the patch classification. They can find a defect, but they weren't capable to identify exactly where this can occur on a wooden frame [15].

Modern frames of object detection have solved this problem. These frames have made possible the localization and classification of objects at the same time, in a single model. The YOLO detectors family has become one of the most practical options for detecting knots. Models based on YOLO are particularly attractive in industrial environments, because they can run in real time, maintaining a solid balance between the detection and the computational efficiency [16].

The recent studies have pushed the YOLO infrastructures. The research has added attention mechanisms [17], backbone transformers [18] and optimization methods such as network pruning and quantization [19]. These improvements allow better running for the models on the hardware also with poor hardware. Other frameworks of object detection such as Faster R-CNN [20] and EfficientDet [21] have been widely used for defect wood inspection. However, implementation in rapid production environment is not common. The main reasons are that their processing and inference speed requirements are small [22-24].

### 2.3. Limitations of Current Research

Despite the last years recorded progress, more challenges have not been solved yet. A great part of literature is focused on improving the detection precision and on performance indicators, but not really on practical implementation. This aspect gets very little attention. Aspects like interference latency, efficiently energetic and integration with execution systems of the MES production are rarely analyzed in depth. Just a limited number of studies are looking into optimization of runtime for hardware platforms at the edge level, such as GPU or TPU, even if these technologies play a key role in automated-timber development and intelligent fabrication environments [25-27].

The interoperability and the integration of the systems present a limitation. Just a small number of proposed solutions produce actual results in a standard form in which other software systems could use them directly, in platforms like CAD instruments, systems of resource planning (ERP) or twin digital environments [28]. This flaw in standardization represents an important barrier in the way of implementation on long-term applications. Without maps of standard and readable defects by machines, systems of inspection based on AI are still difficult to integrate in the larger ecosystem of digital production [29].

## 3. Proposed solution

To automatize knot detection, a Python Flask service was used to integrate pre-processing, inference, annotation and deployment into a single pipeline to also fit industrial use.

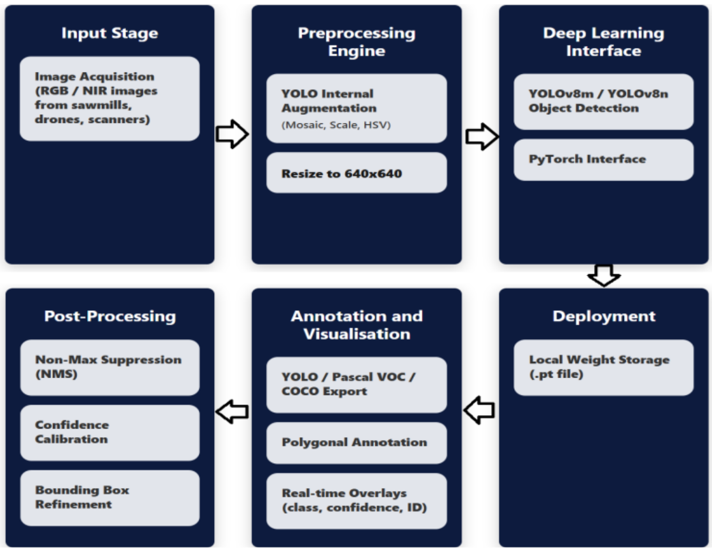


Fig. 1. Proposed system architecture for automated knot detection

Fig. 1 shows the proposed system's flow of events, starting from the input stage, where the image collection happens and ending with the annotation and visualization stage. Following the image acquisition, the images are being resized to 640 x 640 px to fit the YOLO requirements. Next, the two YOLOv8 model variants, medium and nano, achieve object detection with PyTorch inference. In the post-processing stage, there is confidence calibration and bounding box refinement.

In natural environments, wood inspection images are often taken in uncontrolled conditions, with variable lighting, not being able to fully capture its real state. For this study, the trained models are evaluated in their native PyTorch framework (pt format). Both the Nano and Medium variants were trained for 100 epochs to assess the performance of trade-offs directly.

The data set for this study comes from an open-source deposit available to the public, built for researching the defects from wood. Over 20000 images. Over 43000 noted defects. The images present wooden planks photographed in different stages of processing, from the freshly cut timber to polished surfaces. For training, the data set has been divided into subsets of training and validation using a 90/10 ratio. 90 percent of images have trained the models. The remaining 10 percent were reserved for validation. This division permits testing the models on data that has not been seen before, while keeping a sufficiently large training set to keep learning. YOLOv8 is made for balancing the accuracy of the detection with computational efficiency. To analyze this compromise, two variants of the model have been trained in the same experimental conditions: YOLOv8n și YOLOv8m. Both have run through 100 eras on the same division of the data set. This ensured that the comparison between the two architectures stayed consistent and fair.

### 3.1. Defects classification

#### *3.1.1. Live knot*

A live knot, represented in Fig. 2.a., formed from a living branch, while the tree is still growing. The fibers of the trunk continue to grow around the living branch, leading to a tightly bonded knot.

#### *3.1.2. Dead knot*

A dead knot is the complete opposite from a live knot. It forms from a dead branch, and it is not tightly bonded with the surrounding wood. A dead knot is represented in Fig. 2.b.

#### *3.1.3. Knot with crack*

A knot with a crack, represented in Fig. 2.c., is a knot that presents splits either within the knot itself or in the surrounding wood radiating from it. They are often associated with dead or partially dead knots but can also occur in large live knots.

#### *3.1.4. Resin*

Resin, represented in Fig. 2.d., is a sticky or viscous substance produced by trees as a protective behavior in response to injury or stress. It can seal wounds caused by broken branches, cuts or insects; it prevents moisture loss and decay.

#### *3.1.5. Crack*

Fig. 2.e. depicts a crack in wood, which is a separation or fracture of the wood fiber caused by internal stress or external forces, resulting in a visible split.

#### *3.1.6. Missing knot*

A missing knot is a hole in the wood block, where a knot was originally present. Usually, it is caused by a dead knot and because of the poor bonding between the knot and the surrounding wood, the knot has fallen out. Such a void is represented in Fig. 2.f.

#### *3.1.7. Brittle heart*

Brittle heart is a result of compression failure in fibers during growth, represented in Fig. 2.g.

#### *3.1.8. Overgrown knot*

An overgrown knot forms when a branch has been completely enclosed by the surrounding trunk wood. It is larger than usual live knots and because it is intergrown it does not loosen or fall out, causing surrounding wood fibers to bend around the knot and create small stress concentrations. An overgrown knot is represented in Fig. 2.h.

#### *3.1.9. Marrow*

Marrow appears as a small circular or elongated zone at or near the center growth rings, as shown in Fig. 2.i.

*3.1.10. Blue stain*

Blue stain is caused by a fungus that feeds on the sap, and it does not live in the tree due to lack of oxygen (Fig. 2.j.).

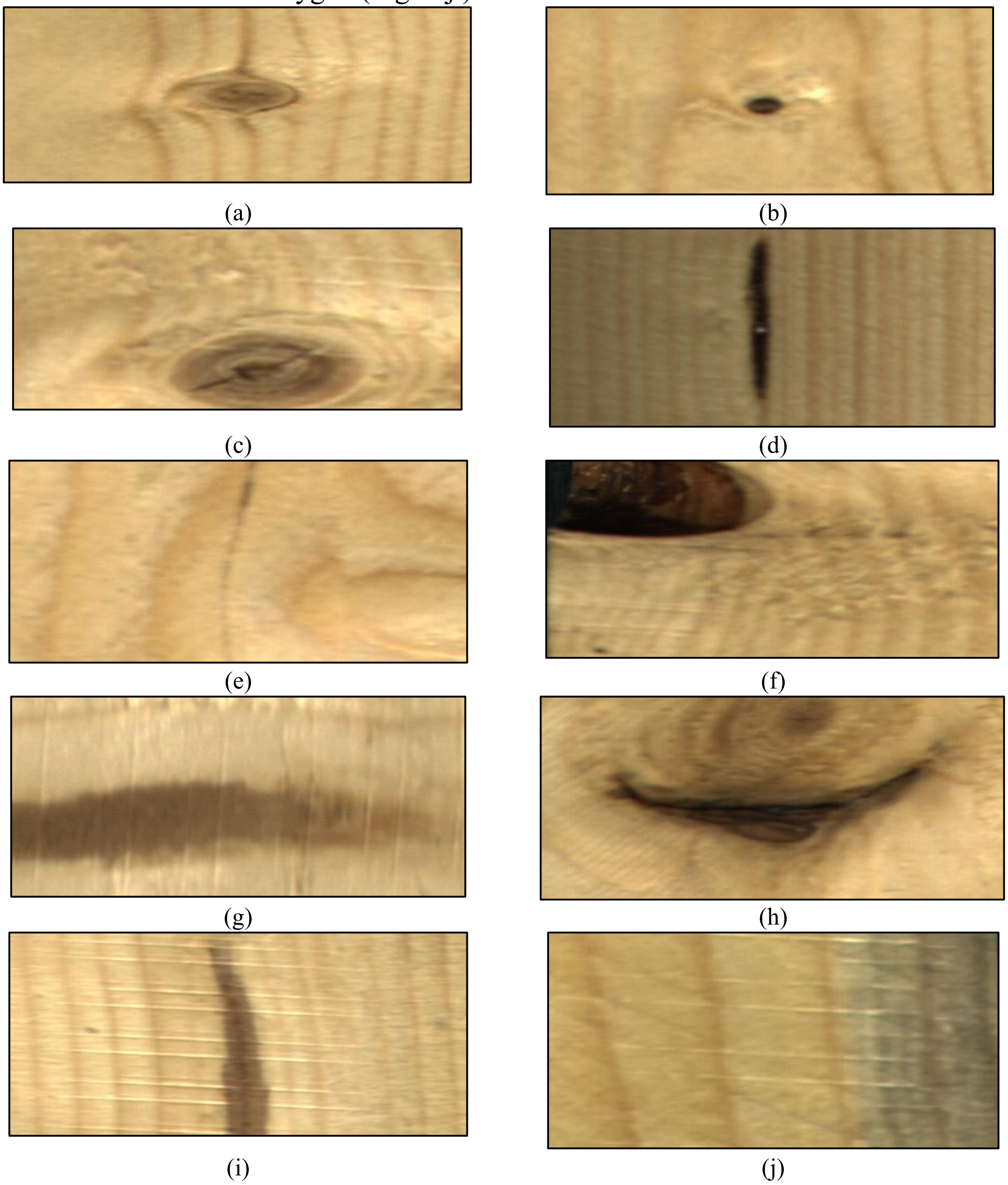



Fig. 2. Defects classification: (a) Live knot; (b) Dead knot; (c) Knot with crack; (d) Resin; (e) Crack; (f) Missing knot; (g) Brittle heart; (h) Overgrown knot; (i) Marrow; (j) Blue stain.

## 4. Results

The performance of the automated knot detection system was evaluated by comparing two architecture variants: the medium-sized variant YOLOv8m and the lightweight YOLOv8n. The evaluation is made on the comparative analysis on the confusion matrix, F1-Confidence Curve, and training and validation curves.

### 4.1. Confusion matrix

In the following Figs. (Fig. 3 and 4), there are presented the confusion matrix for each YOLOv8 model variant, to evaluate their performance side by side. The YOLOv8m achieved 2086 true positives for Live Knot and 991 for Dead Knot, while the YOLOv8n achieved 2137 true positives for Live Knot and 995 for Dead Knot.

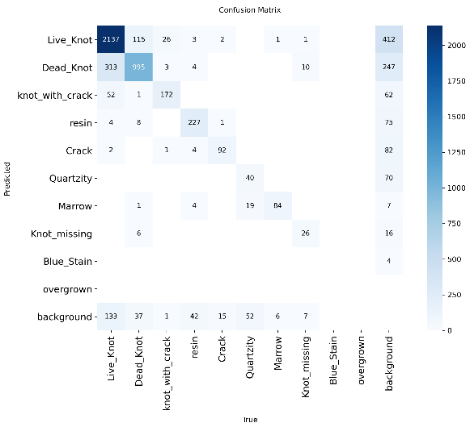



Fig. 3. Confusion matrix YOLOv8m.

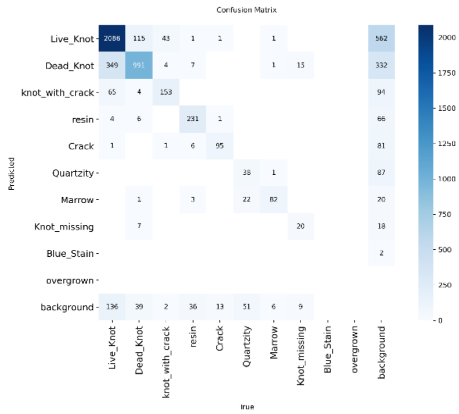



Fig. 4. Confusion matrix YOLOv8n.

Although the two models had similar results, the difference lies in the trade-offs. The YOLOv8m showed class confusion, misclassifying 349 Live Knots as Dead Knots, whilst YOLOv8n misclassified 313 Live knots as Dead Knots. The misclassifications were focused on visually similar categories, such as Live Knot versus Dead Knot.

In addition, the models were also sensitive to differentiating some Live Knots from the background, the nano version achieving 136 false background and the medium version, only 133 false backgrounds. Both models struggled to detect less frequent classes, such as Brittle heart, due to the defect imbalance in the dataset.

### 4.2. Confidence curve

The overall F1 score for YOLOv8m peaks roughly 0.69 at 0.44 confidence. This means that the average detection performance across the entire dataset is good, the model balancing precision and recall.

The overall F1 score for YOLOv8n peaks at 0.7 at 0.621 confidence, which means the average detection performance across the entire dataset is like the medium model.

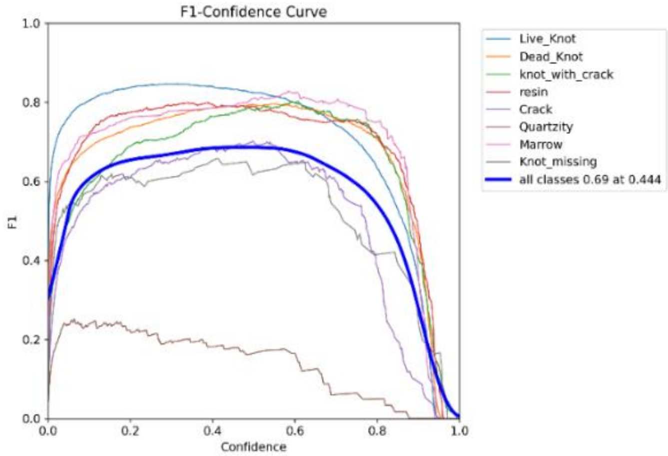



Fig. 5. F1 – Confidence Curve YOLOv8m.

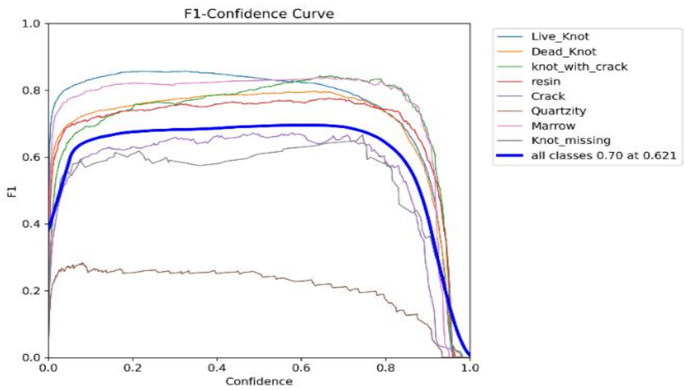
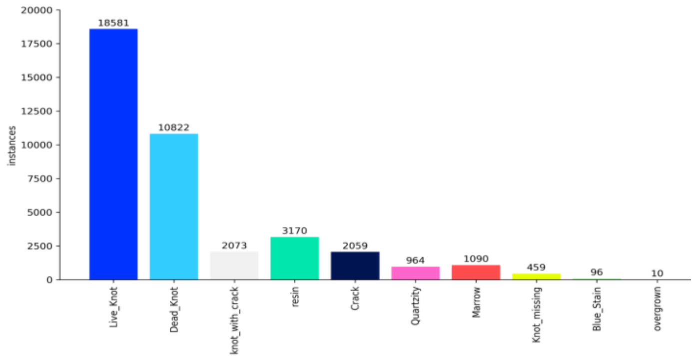



Fig. 6. F1 – Confidence Curve YOLOv8n

The nano model has a higher confidence threshold, which suggests more reliable predictions and reduced sensitivity. The overall detection performance across the most common knot types is more stable and balanced between precision and recall. In addition, Figs. 5 and 6 show the F1 confidence curve for each individual class. Both models had problems detecting the rare defects that are underrepresented in the dataset, such as brittle heart and knot missing, but performed strong on the common classes such as live knot, dead knot or knot with crack.

In Fig. 7 (a) and 8 (a) are illustrated the dataset distribution and annotation statistics for the models of interest. Both YOLOv8n and YOLOv8m show a significant class imbalance, with roughly 18500 live knot images and 10800 dead knot images, while Blue Stain does not reach nearly 10% of the above-mentioned classes. Spatial heatmaps from Fig. 7 (b) and 8 (b) indicate that defects are focused near board centers, while the dimensional analysis confirms most defects are small, relative to the image size. This explains why the model demonstrates high sensitivity for common knots but struggles to generalize for underrepresented classes. Looking at the data set, most defects prove to be quite small. Also, these are frequently grouped close to the central region of the images. A notable model. This spatial concentration suggests that objects which have defects also have the tendency to be compact and closely grouped in the frame, rather than to be spread across all the images. So, these types of characteristics show clearly that the detection techniques should be adapted specially for identification of small objects. Standard detection setups often can't reliably capture these fine-scale defects, and that's a real limitation when working with data like this.

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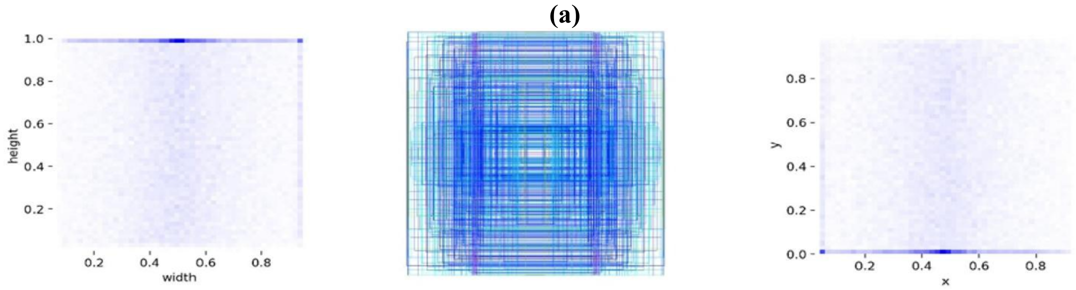
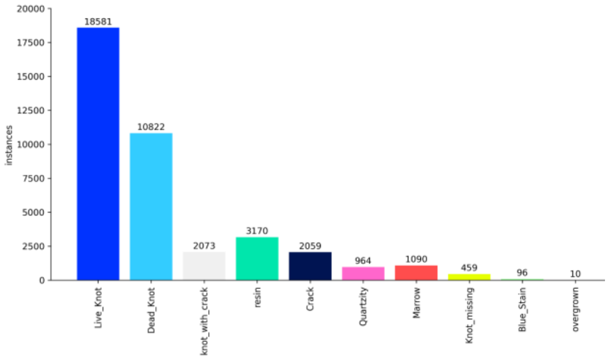



**(b)**

Fig. 7 (a) Dataset distribution and annotation statistics YOLOv8m; (b) Spatial heatmap.

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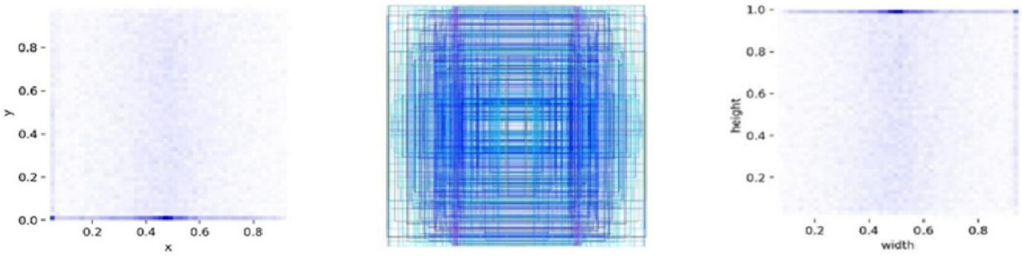



**(b)**

Fig. 8 (a) Dataset distribution and annotation statistics YOLOv8n; (b) Spatial heatmap.

Fig. 9 shows the YOLOv8m model training and validation over 100 epochs, characterizing a stable convergence profile without overfitting significantly.

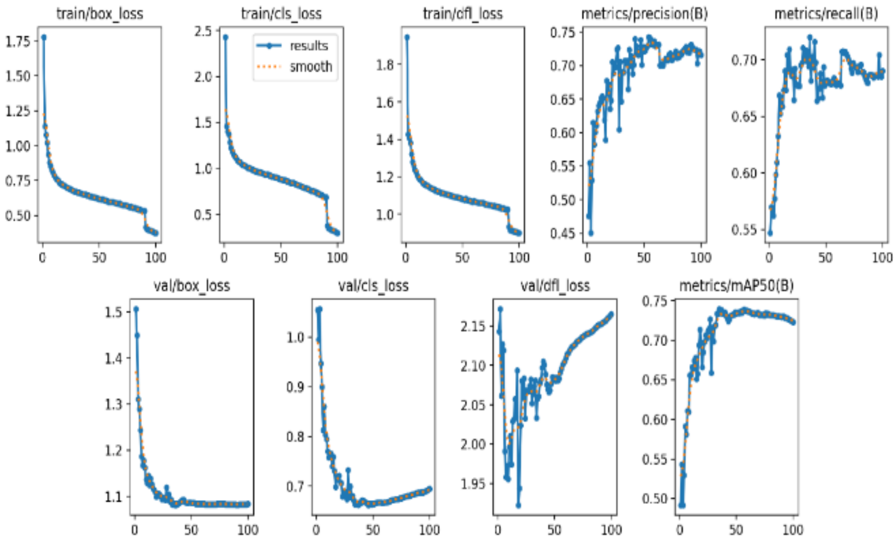



Fig. 9 Training and validation curves for the YOLOv8m knot detection mode.

The evolution of training losses shows a fast decrease in the time of the initial phase of training. This behavior shows that the model is fast learning visual patterns fundamentally associated with knot defects. After the first eras, the rate of decrease becomes more gradual, and the curbs of loss start to stabilize during the 50 era. This stabilization suggests that the model is refining his representations of internal characteristics, instead of learning completely new patterns.

A similar tendency can be observed, also, suddenly at the beginning of the training, before reaching a stable region. The close matching between the curves of loss of training and of validation indicate the fact that the model is generalizing well and that it does not present a significantly over adaptation during the process of training. In parallel with the reduction of the losses, the evaluation metrics, including Precision, Recall, and Mean Average Precision (mAP@50), show constant progress during the process of training. The mAP@50 metric shows a constant improvement all the time during training. The mAP@50 metric gets to approximately 0.74 before stabilizing, suggesting that the model is efficiently converging in the chosen training plan. These results confirm that the horizon of 100 eras is enough for the network to learn the characteristics of the important defects, while maintaining a stable optimization pattern.

Fig. 10 illustrates the dynamic of training of the model YOLOv8n for 100 eras. The image highlights the constant reduction in the training losses, also with a corresponding growth in evaluation metrics. The mAP@50 is getting close to a value of 0.71 and is stabilizing after 50 eras, showing that the model reaches a mature performance stage quite early during the process of training.

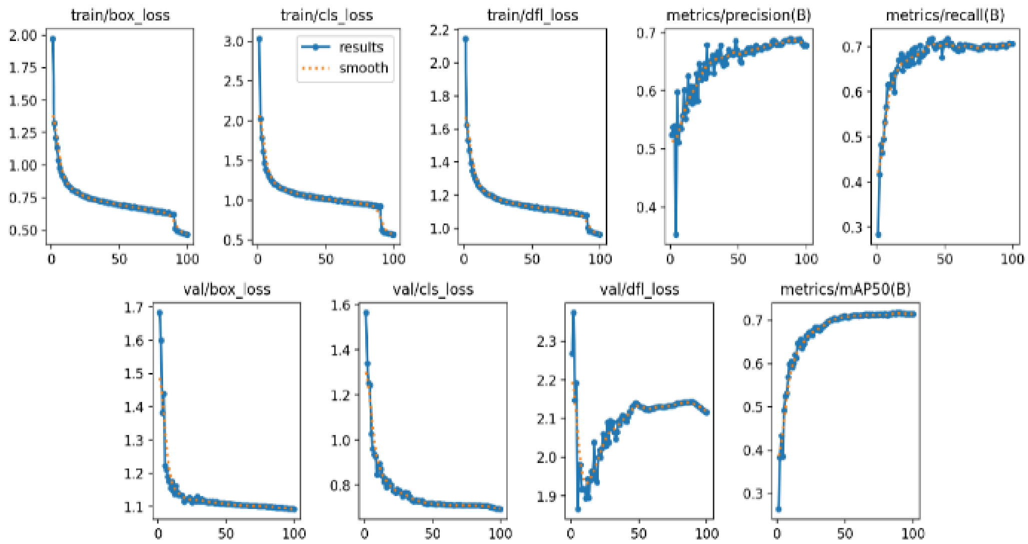
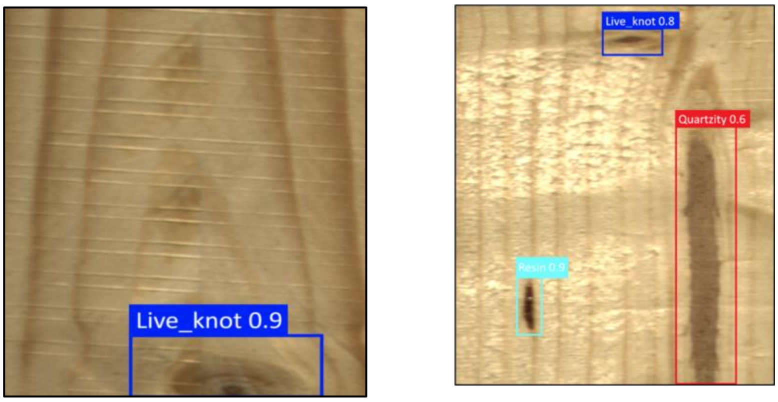



Fig. 10. Training and validation curves for the YOLOv8n knot detection mode.

As for YOLOv8n, the nano model followed a similar path but with less volatility in the validation loss curves. There were fewer parameters used, yet it was still competitive. Its training metrics stayed close behind the medium model, which confirms that the augmentations worked well.

The training dynamics across over 100 epochs show that both models reach stable convergence without major overfitting. This validates the data augmentation that was applied during practice. The model YOLOv8m presents a very strong learning profile. The model YOLOv8M presents a very strong learning profile. Sudden reduction of the loss function is aligned with a constant growth of the performance indicator. Reaching at last a peak of mAP@ 50 of approximately 0.74. This confirms his bigger capacity of modeling complex characteristics of knots. What is notable is the fact that the easy model YOLOv8n follows an identical trajectory. Volatility, even smaller in his losing curves of validation. Even though it has much fewer parameters, the nano model reaches a top of 0.71 mAP@50. This keeps clearly the power discriminative that is necessary for a precise detection, offering at the same time efficiency essential for implementing on edges. The system implements a procedure.of base fitting based on the metric Intersection over Union for comparing the boxes of delimitation detected in two images. The variation of the dimension or the shape of the knot are structure defects that were detected. Differences that were obtained are visualized through maps that are overlapped, which show the way that defects evolve in time, like Fig. 11.




**(a)** **(b)**

Fig. 11. a.b. Output annotated images.

The validation results show that the model YOLOv8 functions favorably in detecting alone defects and also in more complex scenarios with multiple defects. The detector also shows great adaptation at the background noise present usually in wood images. Natural models of wood fiber are in general completely ignored by the model, while the real defects are detected with a high level of trust. For example, alive knots are usually recognized with trust scores close to 0.9, which suggests that the system maintains a stable performance in different visual conditions. This behavior is aligned with the performance characteristic observed in the trust curves

F1. The model can locate multiple types of defects simultaneously while maintaining an efficient inference.

However, prediction certainly varies across categories. Class imbalance in the training dataset limits the confidence levels that the model can achieve for less represented defect types.

A comparison between the YOLOv8m and YOLOv8n architectures reveals a clear trade-off between detection accuracy and computational efficiency. Both models exhibit stable learning behavior during the 100-epoch training process and demonstrate a strong ability to localize small, densely clustered defects, which often appear near the center of wooden board images. This capability suggests that the applied augmentation strategies successfully captured the variability of knot shapes present in the dataset.

Despite these shared characteristics, the two model variants differ in their suitability for specific operational scenarios. The YOLOv8m architecture provides higher detection reliability and is therefore better suited for industrial environments where classification accuracy is critical. The model achieves a peak F1 score of approximately 0.7 at a confidence threshold of 0.621, creating a relatively strict decision boundary that reduces false positives and minimizes background misclassification. With a mAP@50 value close to 0.74, the medium model demonstrates a stronger capacity for distinguishing visually similar defect categories, which is particularly important for strict quality grading processes.

In contrast, the YOLOv8n model emphasizes computational efficiency. Despite its smaller architecture, its evaluation metrics remain close to those of the larger model, achieving a peak F1 score of 0.69 and a mAP@50 of approximately 0.71. This indicates that significant reductions in model size do not necessarily lead to proportional decreases in detection accuracy. However, the nano model requires a lower confidence threshold (0.444) to achieve optimal recall, which introduces slightly higher uncertainty and increases the likelihood of confusion between similar defect classes. Consequently, YOLOv8n is more suitable for real-time edge-computing applications where processing speed and throughput are prioritized over maximum classification precision.

Overall, the comparison confirms that YOLOv8m offers greater stability and reliability for definitive defect grading, while YOLOv8n represents an effective lightweight alternative for resource-constrained monitoring systems.

The multi-class detection results further illustrate the influence of dataset distribution on model confidence. Classes that appear frequently in the training data, such as *Resin* and *Live Knot*, typically reach high confidence scores in the range of 0.8 – 0.9. In contrast, rare defect types such as *Brittle heart* tend to be detected with lower confidence values, around 0.6, reflecting the limited representation of these classes during training.

## 5. Conclusions

In conclusion, this study's purpose was to present a comparative analysis of two out of the 6 YOLOv8 model variants, for knot detection in wooden materials. The YOLOv8n variant achieves a mAP of roughly 0.71 which is slightly lower than the YOLOv8m mAP of 0.73. The detection performance is guided by the F1 score and the confusion matrix, that were again similar. The F1 peak in the nano variant was at 0.69 at 0.444 confidence, while the medium variant peaked at 0.7 at 0.621 confidence. Both model variants struggled with confusion between the Live Knots and Dead Knots, misclassifying the latter with the former. Also, there are significant False Negatives, Live Knots being mistakenly classified as background.

Nevertheless, optimization was not achieved, leaving room for improvement. Future research directions include the adoption of transformer-based architectures, multi-modal sensing and federated learning approaches, as well as the development of human–AI collaboration frameworks that balance efficiency with workforce sustainability.

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