


# Segmentation and Detection of Wooden Surface Defects



By:  
Harshita Jangir  
Gaury Jithesh  
Ayushi Shukla

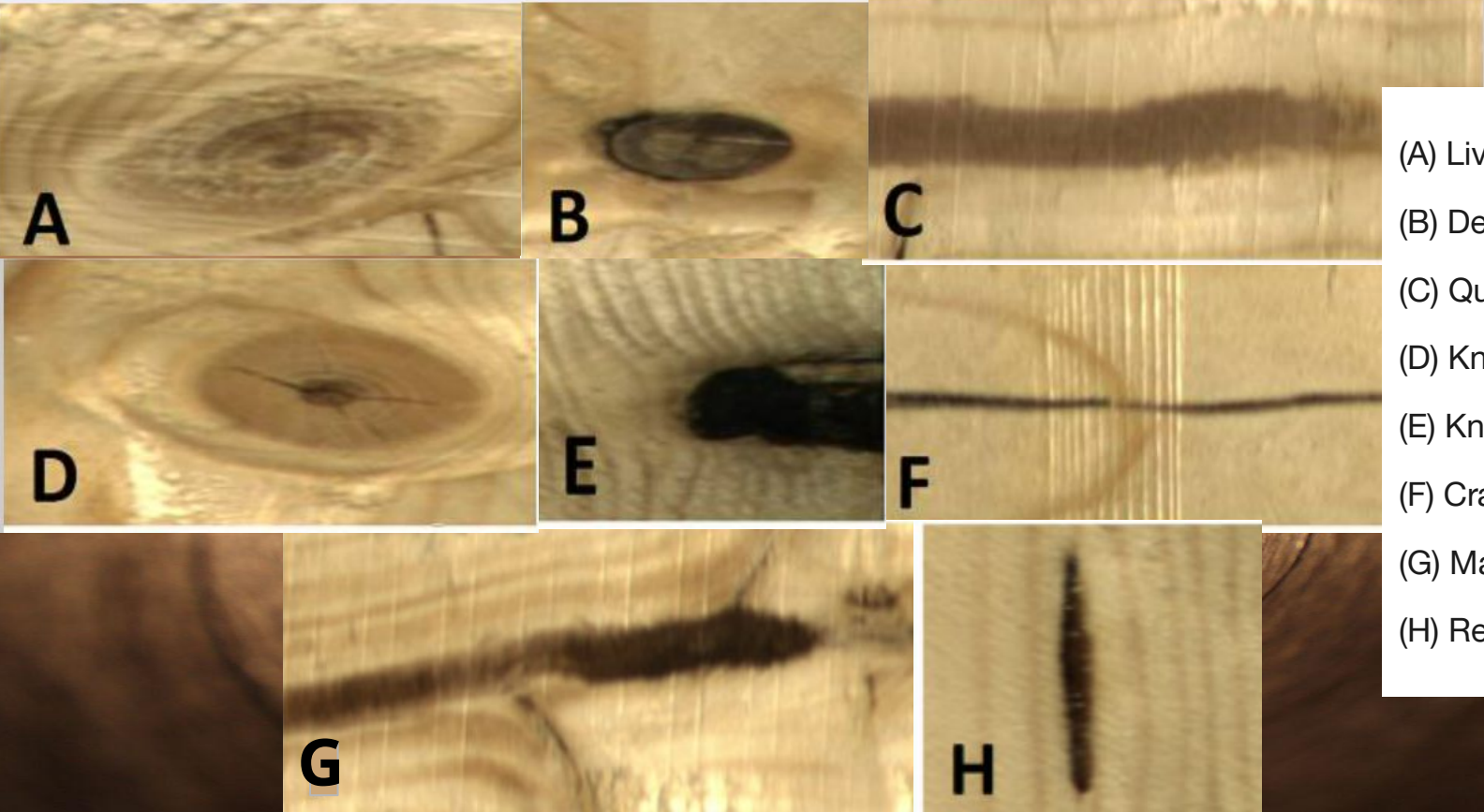
What is the importance of defect detection in wood manufacturing?



# Our Project



The dataset we will use comprises 4,000 images of wooden surfaces, annotated for eight different defect types: Quartzity, Live Knot, Marrow, Resin, Dead Knot, Knot with Crack, Knot Missing, and Crack.



- (A) Live Knot
- (B) Dead Knot
- (C) Quartzity
- (D) Knot with crack
- (E) Knot missing
- (F) Crack
- (G) Marrow
- (H) Resin

8 types of Defects

# Workflow

CV + ML

1. Image Loading and Preprocessing
2. Defect Segmentation
3. Bounding Box Extraction
4. Defect Feature Vector Preparation
5. Defect Classification
6. Visualization



# Version 0.0

## Computer Vision

### 1. Image Loading and Preprocessing

- Remove unnecessary black regions from the left and right edges.
- Convert the cropped image to grayscale using `cv2.cvtColor`.

### 2. Gaussian Blur

- Apply `cv2.GaussianBlur` to reduce noise and smooth the image.

### 3. Global Thresholding

- Apply `cv2.threshold` to create a binary image for further processing.

### 4. Morphological Operations

- Use `cv2.morphologyEx` with a kernel to close small gaps and enhance defect shapes.

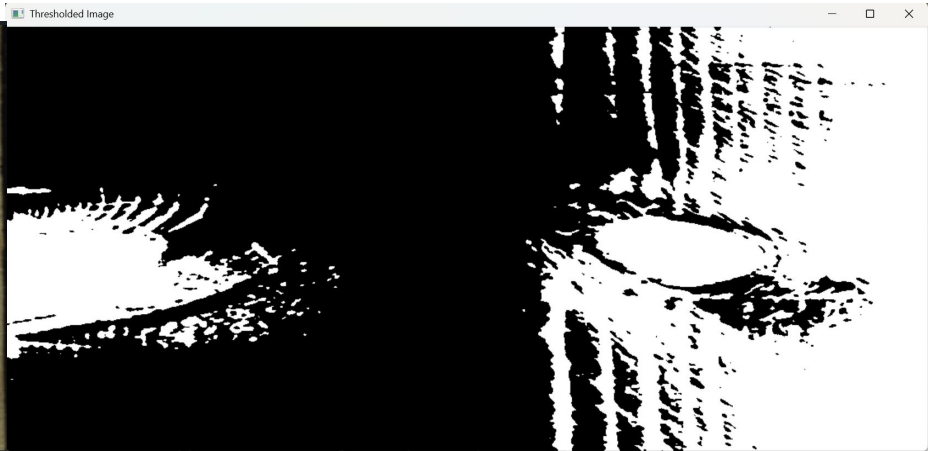
### 5. Contour Detection

- Detect contours using `cv2.findContours`.
- Filter contours based on size to retain only significant defects.

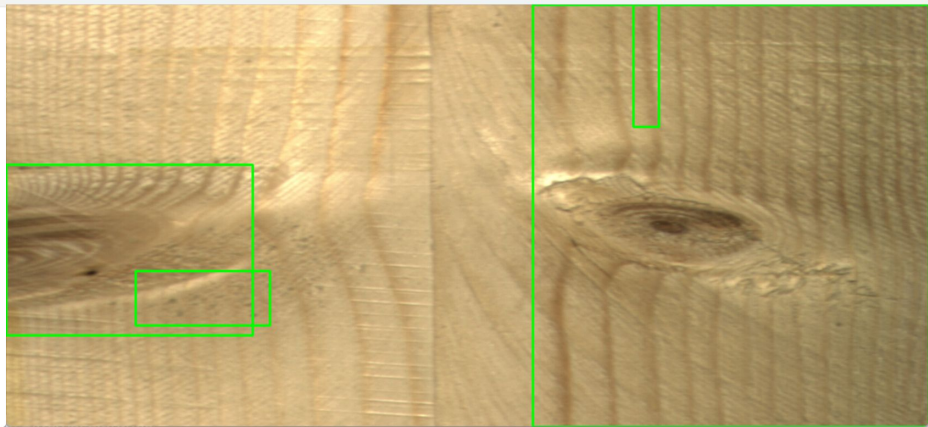




Morphological Operations



Cropped Image with Bounding Boxes



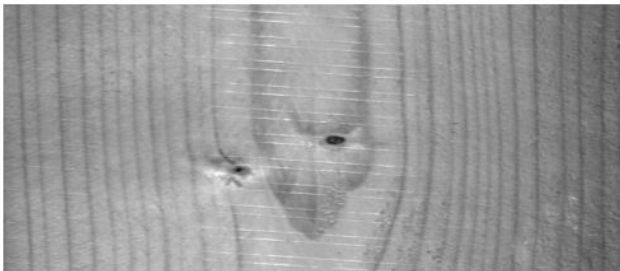


# Version 1.0

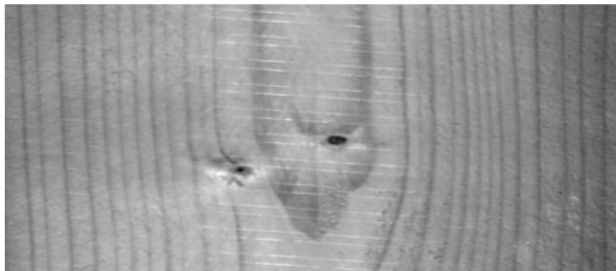
## Computer Vision

- 1. Image Preprocessing**
  - Convert image to grayscale
  - Apply Gaussian blur for noise reduction
- 2. Thresholding Techniques**
  - Global thresholding
  - Otsu's thresholding
  - Adaptive thresholding
- 3. Combination and Refinement**
  - Combine thresholding results using bitwise operations
  - Perform morphological operations (e.g., closing) (using an elliptical kernel) to connect broken parts and fill holes within the detected defects.
- 4. Contour Detection**
  - Detect and filter contours based on size to remove noise
- 5. Feature Extraction**
  - Apply Local Binary Patterns (LBP) for texture analysis
- 6. Defect Classification**
  - Use LBP histograms to classify types of wood defects

Cropped Image



Gaussian Blurred



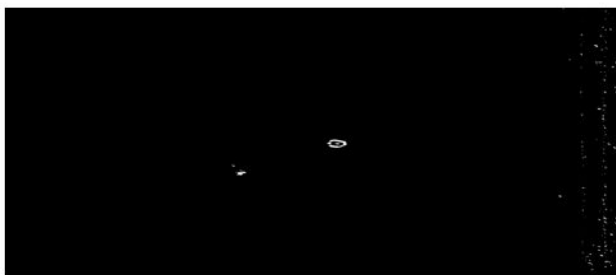
Global Thresholding



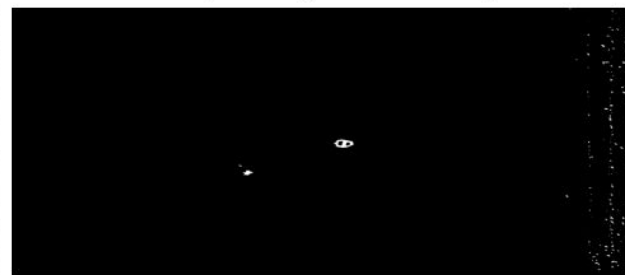
Otsu Thresholding



Combined Threshold



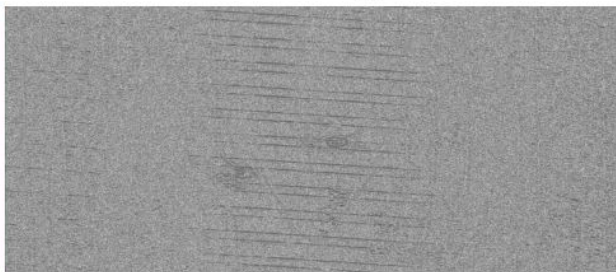
Morphological Closing



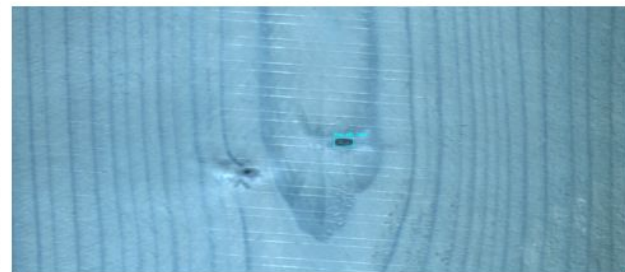
Filtered Contours



LBP Image



Final Result with Defects



# Final Steps Version 2.0

## Computer Vision

1. **Image Preprocessing**
  - Crop 8% from each side to eliminate edge artifacts.
2. **HSV Masking for Color Filtering**
  - Convert the RGB image to HSV.
  - Calculate the median HSV color value of the image.
  - Define lower and upper bounds based on median HSV value.
  - Apply a mask to remove areas similar to the background color.
  - Use bitwise operations to retain defect regions in grayscale.
3. **Noise Reduction with Gaussian Blur**
4. **Thresholding Techniques**
  - Global Thresholding
  - Otsu's Thresholding
  - Adaptive Thresholding
5. **Combination and Refinement**
  - Combine thresholding results.
  - Perform **morphological closing**
6. **Contour Detection**
  - Detect and filter contours based on size to remove noise
7. **Bounding Box Calculation**
  - For each significant contour, calculate a bounding box.
8. **Feature Extraction using Local Binary Patterns (LBP) (Optional)**

Cropped Image



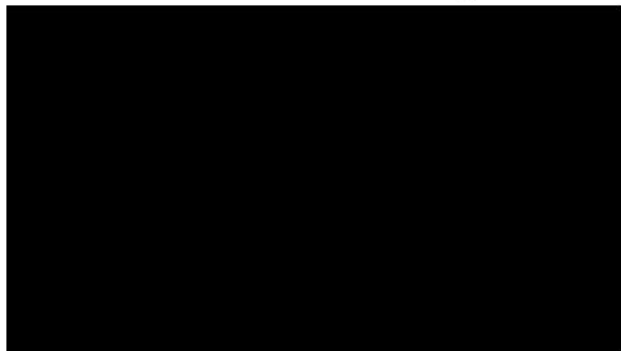
Binary Mask (Inverted)



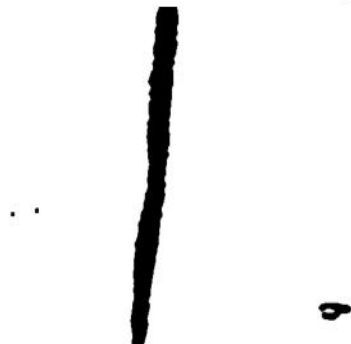
Gaussian Blurred



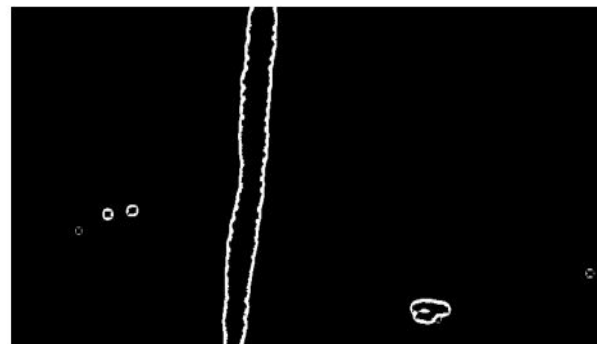
Global Thresholding



Otsu Thresholding



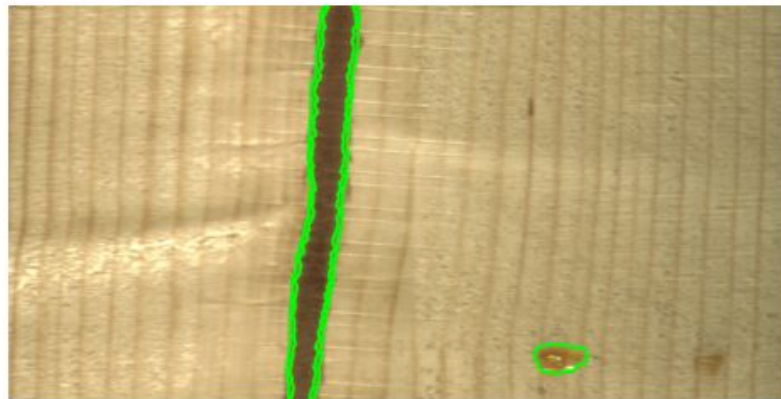
Combined Threshold



Morphological Closing



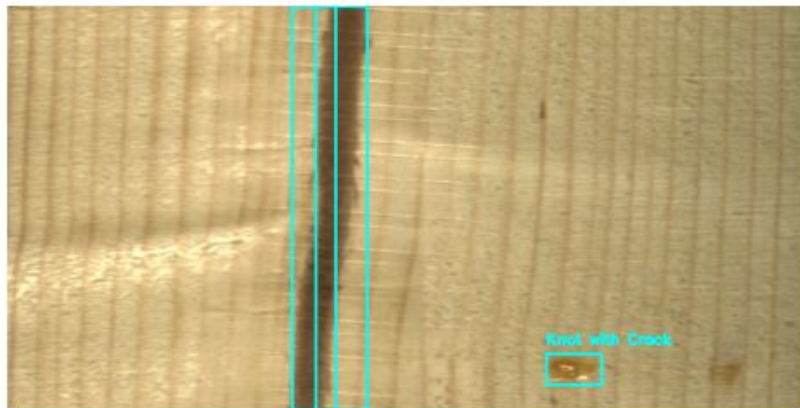
Filtered Contours



LBP Image



Final Result with Defects



# Steps

## Machine Learning

- **Data Loading and Preprocessing**
  - Load bounding box data (x, y, width, height) and defect class labels from CSV and drop unnecessary columns like filename.
- **Feature and Target Separation**
  - Define X as bounding box feature columns: x\_center, y\_center, width, height.
  - Define y as the defect class (target) column.
- **Train-Test Split**
  - Split data into training and testing sets (80-20 split).
- **Model Training**
  - Train models using GridSearchCV for hyperparameter tuning on:
    - Random Forest
    - SVM
    - KNN
    - Decision Tree
- **Prediction and Evaluation**
  - Predict defect classes on the test set for all models.
  - Evaluate each model's performance using a classification report (precision, recall, F1-score for each defect class).
- **Defect Classification in Images**
  - For each bounding box detected in an image, prepare a feature vector (bounding box coordinates).
  - Use all models to classify defect type.
  - Map the predicted class to its corresponding defect label for display.

# Random Forest

64%

## Random Forest Classification Report:

	precision	recall	f1-score	support
Quartzity	0.81	0.40	0.54	42
Live_Knot	0.64	0.84	0.73	819
Marrow	0.42	0.54	0.47	41
Resin	0.71	0.66	0.68	125
Dead_Knot	0.67	0.49	0.57	584
Knot_with_Crack	0.37	0.14	0.21	98
Knot_Missing	0.60	0.25	0.35	24
Crack	0.66	0.57	0.61	110
accuracy			0.64	1843
macro avg	0.61	0.49	0.52	1843
weighted avg	0.64	0.64	0.62	1843

Random Forest Accuracy: 0.64

SVM

61%

## SVM Classification Report:

	precision	recall	f1-score	support
Quartzity	0.91	0.24	0.38	42
Live_Knot	0.62	0.87	0.72	819
Marrow	0.22	0.05	0.08	41
Resin	0.67	0.61	0.64	125
Dead_Knot	0.60	0.42	0.50	584
Knot_with_Crack	0.00	0.00	0.00	98
Knot_Missing	0.00	0.00	0.00	24
Crack	0.53	0.71	0.61	110
accuracy			0.61	1843
macro avg	0.44	0.36	0.37	1843
weighted avg	0.57	0.61	0.57	1843

SVM Accuracy: 0.61



KNN

59%

## KNN Classification Report:

	precision	recall	f1-score	support
Quartzity	0.56	0.33	0.42	42
Live_Knot	0.63	0.76	0.69	819
Marrow	0.33	0.27	0.30	41
Resin	0.68	0.43	0.53	125
Dead_Knot	0.56	0.51	0.53	584
Knot_with_Crack	0.29	0.15	0.20	98
Knot_Missing	0.14	0.04	0.06	24
Crack	0.54	0.56	0.55	110
accuracy			0.59	1843
macro avg	0.47	0.38	0.41	1843
weighted avg	0.57	0.59	0.57	1843

KNN Accuracy: 0.59

# Decision Tree

62%

## Decision Tree Classification Report:

	precision	recall	f1-score	support
Quartzzity	0.68	0.40	0.51	42
Live_Knot	0.63	0.84	0.72	819
Marrow	0.37	0.51	0.43	41
Resin	0.64	0.58	0.61	125
Dead_Knot	0.64	0.44	0.52	584
Knot_with_Crack	0.32	0.11	0.17	98
Knot_Missing	0.40	0.25	0.31	24
Crack	0.67	0.60	0.63	110
accuracy			0.62	1843
macro avg	0.54	0.47	0.49	1843
weighted avg	0.61	0.62	0.60	1843

Decision Tree Accuracy: 0.62

Some Outputs

Decision Tree: Dead\_Knot  
KNN: Dead\_Knot  
SVM: Dead\_Knot  
Random Forest: Dead\_Knot



Decision Tree: Live\_Knot  
KNN: Live\_Knot  
SVM: Live\_Knot  
Random Forest: Live\_Knot



Decision Tree: Dead\_Knot  
KNN: Live\_Knot  
SVM: Live\_Knot  
Random Forest: Dead\_Knot  
Decision Tree: Resin  
KNN: Crack  
SVM: Crack  
Random Forest: Marrow



Decision Tree: Marrow  
KNN: Marrow  
SVM: Crack  
Random Forest: Crack



Decision Tree: Resin  
KNN: Resin  
SVM: Resin  
Random Forest: Resin



Decision Tree: Crack  
KNN: Resin  
SVM: Resin  
Random Forest: Resin

Decision Tree: Dead\_Knot  
KNN: Dead\_Knot  
SVM: Live\_Knot  
Random Forest: Dead\_Knot



Decision Tree: Resin  
KNN: Quartzity  
SVM: Resin  
Random Forest: Resin



Some Outputs with Errors



Decision Tree: Dead\_Knot  
KNN: Dead\_Knot  
SVM: Dead\_Knot  
Random Forest: Resin



Decision Tree: Resin  
KNN: Dead\_Knot  
SVM: Dead\_Knot  
Random Forest: Dead\_Knot



Decision Tree: Live\_Knot  
KNN: Crack  
SVM: Marrow  
Random Forest: Marrow

Decision Tree: Dead\_Knot  
KNN: Live\_Knot  
SVM: Live\_Knot  
Random Forest: Dead\_Knot

Decision Tree: Live\_Knot  
KNN: Live\_Knot  
SVM: Live\_Knot  
Random Forest: Live\_Knot

Decision Tree: Live\_Knot  
KNN: Dead\_Knot  
SVM: Live\_Knot  
Random Forest: Live\_Knot

Decision Tree: Dead\_Knot  
KNN: Live\_Knot  
SVM: Live\_Knot  
Random Forest: Dead\_Knot

Decision Tree: Resin  
KNN: Resin  
SVM: Resin  
Random Forest: Resin

Decision Tree: Live\_Knot  
KNN: Dead\_Knot  
SVM: Dead\_Knot  
Random Forest: Dead\_Knot

# Comparison with Deep Learning Models

# Challenges and Limitations

## Challenges

- **Feature Consistency**
  - LBP addition changes feature set; requires retraining for consistency.
- **Lighting & Image Quality**
  - Segmentation affected by varying lighting conditions; needs robust pre-processing.
- **Thresholding & Segmentation**
- **Contour Filtering**
  - Fixed contour size thresholds may miss defects or capture noise.
- **LBP Texture Extraction**
  - Limited performance on low-contrast textures; may miss subtle details.

## Limitations

- **Class Imbalance**
  - Rare defect types lead to skewed classification results.
- **Computational Load**
  - High resource demands; challenging for real-time or large-scale data.
- **Bounding Box Accuracy**
  - Inaccurate bounding boxes impact defect classification reliability.
- **Generalization**
  - Limited adaptability to new wood types and defect patterns.





# Insights, Future Work and Improvements



# Conclusion

This project developed a method to detect and classify wood surface defects by combining computer vision techniques with machine learning models. Key steps included using HSV color masking, thresholding, and morphological operations to segment defects, while Local Binary Patterns (LBP) helped extract meaningful features. Both Random Forest and SVM classifiers performed well in distinguishing defect types, demonstrating the effectiveness of classical methods in industrial applications. This solution can streamline quality control in woodworking, offering an efficient and interpretable alternative to manual inspection.