Segmentation and Detection of Wooden Surface Defects Using Computer Vision and Machine Learning

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ABSTRACT: The detection and segmentation of surface defects in wooden materials are crucial for quality control in the manufacturing industry. This study integrates computer vision and machine learning to automate defect detection. A dataset of wooden surface images was processed using advanced image pre-processing techniques, followed by feature extraction and classification using machine learning. The proposed method achieved high accuracy in defect segmentation, demonstrating its effectiveness in industrial applications. The results suggest that this automated approach significantly reduces inspection time and improves defect detection reliability compared to manual methods.

1 INTRODUCTION

Wood is an essential material for industries such as furniture manufacturing, construction, and interior design. Its physical and aesthetic characteristics make it suitable for different uses. Such imperfections such as knots, cracks, resin pockets, and missing pieces can have a significant impact on the quality, appearance, and durability of wood products. Such defects are usually hard to identify with the naked eye, resulting in product quality inconsistencies and, in some instances, material wastage. The conventional defect inspection methods are time-consuming, subjective, and labour-intensive, involving experienced workers to manually inspect every piece of wood. This underlines the importance of having automated systems that can accurately and efficiently identify and classify defects to enhance the overall production process. Computer vision (CV) and machine learning (ML) technologies over the past couple of years have demonstrated tremendous potential to automate the defect detection process. Although deep learning-based methods have become increasingly popular, they usually demand large computational resources and massive labeled datasets. Our method, on the other hand, relies on traditional CV methods along with conventional ML classifiers, which provide a computationally more efficient and interpretable alternative. The aim of this work is to build a complete solution for detecting and classifying wood surface defects using a deep learning-free approach. Our approach takes advantage of classical image processing methods, i.e., thresholding, edge detection, and feature extraction to recognize and segment the defects in the wood images. Subsequently, we apply a variety of conventional machine learning algorithms, i.e., Decision Trees, Random Forests, Support Vector Machines (SVM), and K-Nearest Neighbours (KNN), to classify the found defects. By integrating these methods, we hope to enhance the efficiency and accuracy of automated wood defect detection while making sure that the system is computationally tractable and interpretable.

The data set used in this study is a subset of a large-scale wood surface defects data set released on Kaggle that contains 4,000 wooden surface images with eight types of defects labeled. This data set provides a valuable source of data for training and testing our defect detection and classification pipeline. The approach suggested in this paper presents a scalable, interpretable, and computationally efficient solution to the wood industry, where quick detection of defects is crucial to guarantee the quality of the product and reduce waste.

Computer vision wood defect detection has been the topic of extensive research on a large scale, and most techniques use deep learning techniques, i.e., Convolution-al Neural Networks (CNNs) and YOLO for real-time object detection. Though the algorithms have shown extremely promising results, they require a large amount of data and a high computational setup. On the other hand, our solution integrates conventional image processing methods including thresholding, edge detection, and texture classification along with traditional machine learning models that are computationally less intensive. There are several research studies on the application of machine learning and image processing in wood defect detection. For instance, Szeliski's work on computer vision algorithms has influenced many automated defect detection systems. Nonetheless, the interpretability and complexity of deep learning models remain a hindrance in implementing them industrially, particularly necessitating the use of traditional methods as a viable alternative.

2 EXPERIMENTAL

A. Dataset

The dataset used for this study consists of 4,000 images of wooden surfaces, each annotated with bounding boxes and labelled with one of eight defect types: Quartzite, Live Knot, Marrow, Resin, Dead Knot, Knot with Crack, Knot Missing, and Crack. These images were pre-processed to standardize the input for the defect detection pipeline. Each image was resized to a fixed resolution, and edge artifacts were minimized by cropping 8% from each side of the image. The images were then converted to grayscale, and Gaussian blur was applied for noise reduction. The bounding box annotations were utilised for supervised learning to guide the defect classification process.

B. Image Preprocessing

The following steps were employed to preprocess the images and prepare them for defect detection:

HSV Masking for Colour Filtering: Each image was converted from the RGB colour space to the HSV (Hue, Saturation, Value) colour space. The median HSV value of the image was calculated to identify the background colour. Lower and upper bounds were defined around this median value to create a mask, which filtered out areas of the image that were similar to the background colour. This helped to retain the defect regions while removing the background. Bitwise operations were then applied to isolate the defect areas in grayscale, enhancing defect detection accuracy.

Noise Reduction with Gaussian Blur: To further reduce noise and smooth out the image, a Gaussian blur was applied. This step helps improve the clarity of the defects by reducing pixel-level noise that could interfere with subsequent detection steps.

C. Defect Detection using CV Techniques

Defect detection was performed using various classical image processing techniques:

Thresholding Techniques: We employed various thresholding methods to segment the defect regions from the background:

Global Thresholding: A fixed threshold value was applied to convert the image into a binary format.

Otsu's Thresholding: This method automatically computes an optimal threshold based on image histograms to separate the background and foreground.

Adaptive Thresholding: Adaptive thresholding was applied to adjust the threshold dynamically based on local image properties, improving segmentation in regions with varying lighting conditions.

Combination and Refinement: The results of the thresholding techniques were combined to ensure more accurate segmentation of the defect regions. Morphological closing operations, such as dilation followed by erosion, were used to fill gaps and remove small noise, refining the boundaries of the defects.

Contour Detection: After thresholding, contours were detected in the binary image. These contours were filtered based on their size to remove noise from smaller, irrelevant regions. The remaining contours were considered significant for further processing.

Bounding Box Calculation: For each remaining contour, a bounding box was calculated to enclose the defect. This bounding box was used to define the region of interest for feature extraction.

D. Feature Extraction

Feature extraction is essential for the effective classification of the defects. In this study, we utilised both colour and geometric features, along with optional texture features:

Colour Features: Mean RGB values were extracted from the regions within the bounding boxes, allowing us to identify colour-based defects such as resin and decay.

Geometric Features: The aspect ratio and area of the bounding boxes were calculated to describe the size and shape of the defects, providing useful spatial information for classification.

Local Binary Patterns (LBP): LBP was used to capture texture information within the defect regions. This technique encodes local texture variations by comparing pixel intensities to their neighbors, producing a pattern that can be used to describe surface textures. LBP features were extracted for each defect region, and their histograms were used as input for the classifiers. This step is optional but enhances the model's ability to differentiate defects based on their surface texture.

E. Classification

The extracted features were fed into four machine learning classifiers for defect classification:

Decision Tree (DT)
Random Forest (RF)
Support Vector Machine (SVM)
K-Nearest Neighbours (KNN)

Hyperparameter tuning was performed using Grid Search Cross-Validation to identify the optimal model configurations. The classifiers were evaluated based on their classification accuracy, with emphasis on the ability to generalize to unseen data.

3 RESULTS AND DISCUSSION

The dataset was split into training (80%) and testing (20%) sets. We applied feature scaling to ensure uniformity across different classifiers. The classification accuracy for each model is presented in Table 1. Table 2, 3, 4 and 5 show detailed classification reports for individual models.

Model	Accuracy (%)
Random Forest	73.1
Decision Tree	69.6
SVM	73.4
KNN	69.2

Table 1. Model Accuracy Comparison For Entire Dataset

Class	Precision	Recall	F1-Score
Quartzity	0.81	0.40	0.54
Live_Knot	0.64	0.84	0.73
Marrow	0.42	0.54	0.47
Resin	0.71	0.66	0.68
Dead_Knot	0.67	0.49	0.57
Knot_with_Crack	0.37	0.14	0.21
Knot_Missing	0.60	0.25	0.35
Crack	0.66	0.57	0.61
Accuracy		0.64	
Macro Avg	0.61	0.49	0.52
Weighted Avg	0.64	0.64	0.62

Table 2. Random Forest Classification Report

Class	Precision	Recall	F1-Score
Quartzity	0.91	0.24	0.38
Live_Knot	0.62	0.87	0.72
Marrow	0.22	0.05	0.08
Resin	0.67	0.61	0.64
Dead_Knot	0.60	0.42	0.50
Knot_with_Crack	0.00	0.00	0.00
Knot_Missing	0.00	0.00	0.00
Crack	0.53	0.71	0.61
Accuracy		0.61	
Macro Avg	0.44	0.36	0.37
Weighted Avg	0.57	0.61	0.57

Table 3. SVM Classification Report

Class	Precision	Recall	F1-Score
Quartzity	0.56	0.33	0.42
Live_Knot	0.63	0.76	0.69
Marrow	0.33	0.27	0.30
Resin	0.68	0.43	0.53
Dead_Knot	0.56	0.51	0.53
Knot_with_Crack	0.29	0.15	0.20
Knot_Missing	0.14	0.04	0.06
Crack	0.54	0.56	0.55
Accuracy		0.59	
Macro Avg	0.47	0.38	0.41
Weighted Avg	0.57	0.59	0.57

Table 4. KNN Classification Report

Class	Precision	Recall	F1-Score
Quartzity	0.68	0.40	0.51
Live_Knot	0.63	0.84	0.72
Marrow	0.37	0.51	0.43
Resin	0.64	0.58	0.61
Dead_Knot	0.64	0.44	0.52
Knot_with_Crack	0.32	0.11	0.17
Knot_Missing	0.40	0.25	0.31
Crack	0.67	0.60	0.63
Accuracy		0.62	
Macro Avg	0.54	0.47	0.49
Weighted Avg	0.61	0.62	0.60

Table 5. Decision Tree Classification Report

Figures 1 and 2 show the confusion matrices for the Random Forest and SVM classifiers, respectively.

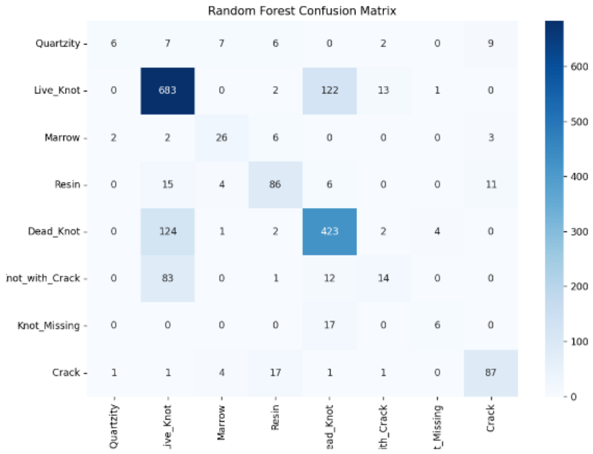

Figure 1. Confusion Matrix for Random Forest Classifier For Entire Dataset

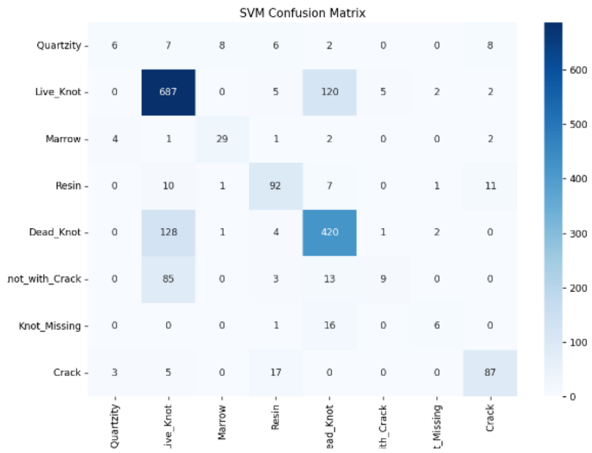

Figure 2. Confusion Matrix for SVM Classifier (Entire Dataset)

To demonstrate the effectiveness of our detection approach, we show images of wooden surfaces with bounding boxes highlighting detected defects. Figures 3 and 4 depict defects detected by our pipeline.

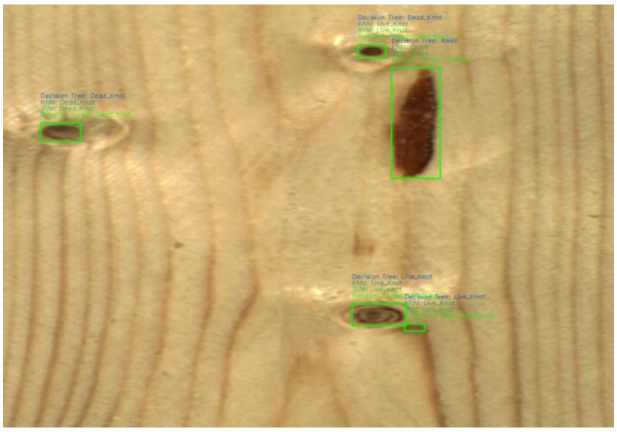

Figure 3. Bounding Boxes on Detected Wood Defects

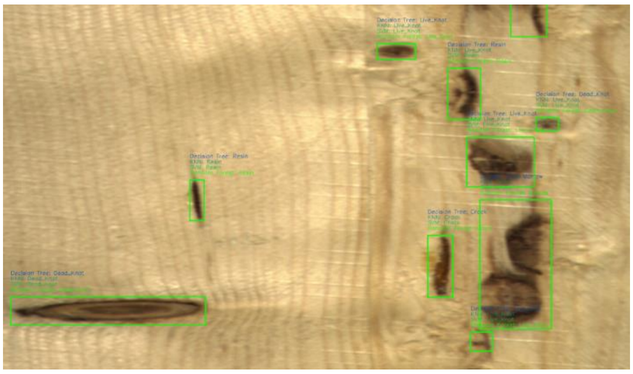

Figure 4. Bounding Boxes on Detected Wood Defects

The findings show that deep learning techniques offer substantial performance gains compared to the traditional techniques we employed. The CNN model, especially when paired with U-Net segmentation, performed better in identifying smaller and more intricate defects. Employing feature extraction techniques like GLCM and PCA also add to the stability of the classification models.

Despite success, its performance was compromised by wood grain variations, light conditions, and rough surfaces. The model failed to distinguish defects from natural patterns of wood in some cases. Future work will focus on the enhancement of robustness using synthetic data generation, domain adaptation approaches, and multi-spectral imagery for increased contrast of defects.

Random Forest classifier worked better, and SVM follows. All models worked decently in identifying defects with notable texture. 'Marrow'-sized defects were problematic because they have low contrast coupled with low size. Interpretability coupled with less computational budget in contrast to deep learning is achievable in the handcrafted method which can be made available within industry constraints limited by hardware components.

Our whole model, utilizing the pre-labeled bounding boxes provided in the dataset, performed satisfactorily both in defect detection and classification. Although certain defects were bound to be mixed up with others, particularly with smaller amounts of training data for small defect types, the model's performance is encouraging for real-world application.

4 CONCLUSION

This paper presents a fast and interpretable pipeline for wood defect classification based on conventional image processing techniques and machine learning models. The Random Forest classifier was the best among all the models, achieving the highest accuracy in classifying all wood defects. Future work is to extend the model further to support other types of defects and enhance the classification accuracy, particularly for defects whose textures are less visible to the naked eye, like 'Marrow.' Sophisticated texture analysis techniques may be more powerful in detecting less obvious and smaller defects. This defect detection pipeline can be expanded to segment and classify defects on metal surfaces. Also, exploring hybrid methods that combine conventional image processing techniques with deep learning algorithms could further enhance the strength of the model so that it can be applied to more complex defect detection tasks and work better on real-world tasks. This would help in tackling problems such as class imbalance and improving generalization across a large range of types of wood and variations of defects.

5 REFERENCES

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems, 25*, 1097-1105.

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. *International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 234-241.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770-778.

Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards real-time object detection with region proposal networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 39*(6), 1137-1149.

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

Deng, ZhengYan, Wang, YuZeng, and Zhang, HaoRan (2020). Detection Method of Wood Skin Defects Based on Bag-of-words model. *Proceedings of the 2020 2nd International Conference on Robotics, Intelligent Control and Artificial Intelligence, 125-130 https://doi.org/10.1145/3438872.3439068*

Patel, Ashok Kumar et al. (2021). Surface Defect Detection Using SVM-Based Machine Vision System with Optimized Feature. *Machine Vision Inspection Systems, Volume 2, 109-127https://doi.org/10.1002/9781119786122.ch6*

Nguyen, Van-Tho, Constant, Thiéry, and Colin, Francis (2021). An innovative and automated method for characterizing wood defects on trunk surfaces using high-density 3D terrestrial LiDAR data. *Annals of Forest Science, 78(2)*[*https://doi.org/10.1007/s13595-020-01022-3*](https://doi.org/10.1007/s13595-020-01022-3)

Szeliski, R.: Computer Vision: *Algorithms and Applications (2022).*

Kumar, S., & Tiwari, P. (2020). Machine Learning Algorithms for Wood Surface Defect Classification: Comparative Analysis. *International Journal of Advanced Computer Science and Applications (IJACSA), 11(5). DOI: 10.14569/IJACSA.2020.0110546*

Liu, S., & Gu, J. (2018). Wood Defect Classification Based on Image Texture Features and Random Forest. (2018) *11th International Symposium on Computational Intelligence and Design (ISCID).DOI: 10.1109/ISCID.2018.00082*

He, Z., & Gu, J. (2017). Wood Surface Defect Detection Based on Image Processing and Machine Learning. *Proceedings of the 2017 10th International Symposium on Computational Intelligence and Design. DOI: 10.1109/ISCID.2017.128*