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Real-Time Defect Detection and Classification on Wood Surfaces Using Deep Learning

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Abstract

This paper proposes a novel method for automatic real-time defect detection and classification on wood surfaces. Our method uses deep convolutional neural network (CNN) based approach Faster R-CNN (Region-based CNN) as detector and MobileNetV3 as backbone network for feature extraction. The key difference of our approach from the existing methods is that it detects knots and other type of defects efficiently and does the classification in real-time from the input video frames. Speed and accuracy is the main focus of our work. In the case of the industrial quality control and inspection such as defects detection, the task of detection and classification needs to be done in real-time on a computationally limited processing units or commodity processors. Our trained model is a light weight, and it can even be deployed on systems for example mobile and edge devices. We have pre-trained the MobileNet V3 on large image dataset for feature extraction. We use Faster R-CNN for detection and classification of defects. The system does the real-time detection and classification on an average of 37 frames per second from input video frames, using low cost and low memory GPU (Graphics Processing Unit). Our method has achieved an overall accuracy of 99% in detecting and classifying defects.

I Introduction

Inspection of the product's surface for defects is a crucial step in industrial quality control, because it ensures the consistency of the final product's quality and the efficiency of the manufacturing process. Identifying and removing defective items from the production line as early as possible is essential; otherwise, they will have a negative impact on the subsequent assembly line and lower overall quality. Even though wood is a valuable natural resource, flaws in wood products can have a significant impact on the commercial value of a product. Live knots, dead knots, and cracks in wood panels can occur as a result of poor raw material quality and ineffective manufacturing processes, among other things. In some developing countries, the use of raw wood materials is reduced as a result of these flaws. Quality inspections of the visual kind are still primarily carried out by trained personnel in the wood processing industry. A robust wood defect detection and identification systems is required by modern wood panels processing industries in order to increase the production rate and revenue. The wood products of today are manufactured in accordance with ever-stricter surface processing specifications than those of the past. As a result, in developed countries with abundant forest resources such as Sweden and Finland, the overall rate of wood consumption can reach 90%. However, in practical applications, the ability to detect defects was insufficient, necessitating the classification of different types of wood defects. Wood defects can take on a variety of shapes and sizes. In addition to knot, stain, holes, cracks, and wane, there are many different types of wood defects to look out for. Different types of wood defects require different levels of processing. Convolutional neural networks have been used to detect defects in industrial products such as wood, steel, and other materials by a number of researchers. While the majority of people use an offline methods which only process single image at a time and such systems are impractical to use in real industrial use cases where wood panels are moving on conveyer belt in large quantities. On the other hand, our novel method detects and classifies defects in real-time, making it suitable for deployment in industry using resource-constrained devices. Our research work has the following major contributions:

- A novel end-to-end deep learning model that can detect and classify defects on wood surfaces in real-time, achieving an overall accuracy of 99%, was proposed.
- A dataset of labeled ground truth images, containing different types of defects was created.

The paper is organized as follows. Section II reviews the some of the most recent related works. Section III describes in details our novel method for defect detection and classification. Section IV analyzes the results of this paper. Finally, Section V concludes the paper and sketches some future research work ideas.

II Related Work

Many deep learning and other statistical methods for defect detection have been proposed. The problem of defect detection and classification have been approached in many different ways by using traditional methods such as k-means clustering, active contours, region growing and graph cuts. Recently the problem has been approached using deep learning methods such as convolutional neural network, encoder-decoder based methods, R-CNN models, recurrent neural networks-based models and generative adversarial network based models. Most of these proposed methods are offline methods, that take single image as an input and then classify, detect and segment. These methods considered efficiency as trivial, which is the key consideration in real-time applications for industrial use case.

Statistical method such as [1] uses fuzzy connected components to detect defects on strip steel surfaces. By combining the pixel connectivity, it is possible to find defects by calculating the maximum and sum of fuzzy connected areas. According to the results of the experiments, the proposed method has a high detection rate of 96.8 percent. A quality evaluation system for slate slabs is described in [2], which was built using artificial vision technology. It is based on the acquisition of 3D and color 2D data, which is then subjected to image processing procedures before being analyzed and reported on. The developed algorithms can successfully detect the six traits considered in this paper: they are capable of characterizing slate slabs in terms of quality grades. An unsupervised method was proposed in [3] for detecting defects from images by focusing on surface texture and using low-rank representation with texture prior. The method's performance is partially dependent on the quality of the prior map, and the method assumes that the defects are in the foreground, which means that if the defect is more significant than the background, the method may fail to detect it and the defect will remain undetected. Random decision forests methods [4] are also used for defect detection. The method uses a combination of feature extraction and classification techniques to detect defects in fabrics. In particular, random decision forests (RDFs) can handle both continuous and discrete variables, it does not overfit as a classifier, and it runs quickly and efficiently when dealing with large datasets. Traditional classification method such as local binary pattern (LBP) is also used for defect classification on the surface of birch veneer [5]. The proposed method only classifies two types of defects i.e. cracks and mineral lines and does not classify other kinds of defects which is the key limitation of the proposed method. To determine the defect area in an image, the gradient local binary pattern (GLBP) [6] is proposed. The method exploits the non-continuity of pixels within a local area. This greatly reduces the scope of the defect existence area, saving time for further defect detection and improving accuracy at the same time. Detection of defects on complex pattern [7] surfaces such as fabrics were also proposed using traditional statistical methods.

In addition to traditional methods the problem of defect detection was also approached using deep learning methods. Most deep learning based models were originally trained for detecting different objects of interests such as people, animals, cars and other objects from real world scenes. These models are trained on large scale image datasets such as MS-COCO [8], ILSVRC [9] and many others. For defect detection and other industrial quality assurance use cases, these pre-trained models were then retrained using a technique called transfer learning for the required target task i.e. defect detection and classification. Most of the recent existing methods use transfer learning and train convolutional neural network based deep learning models such as ResNet [10], RetinaNet [11], AlexNet [12], DenseNet [13], VGG16 [14] and GoogleNet [15] to detect, classify and segments defects. The result from these shows that all CNN based deep learning methods significantly improve the final prediction accuracy of the detection of defects as compared with the traditional methods.

Wood knot detection and classification method based on residual network, called TL-ResNet34 [16], is proposed. Results from the method claims that TL-ResNet34 is far more accurate than other methods for the detection and classification. A weakly supervised CNN based method was proposed in [17] for detection and classification. The model is trained with small number of labelled images. One of the limitations of this method is underfitting, where the model fails to detect and classify different types of defects. An automatic visual inspection system [18] was proposed that can be used to detect and classify defects on wood surfaces. The main contribution of the method is the speed optimization of the defect identification task. The results showed that data augmentation and transfer learning techniques could be used together to achieve good results. The pre-trained ResNet152 neural network model achieved an average accuracy of 80.6%.

A deep regression and classification-based framework for defect detection has been developed in [19] that has four modules i.e detection, false positive reduction, connected component analysis and classification. The proposed method has good accuracy, but it is too computationally for even small size of input image and thus it is limited to offline usage. Another method [20] combines neural architecture search and one of most famous instance segmentation method Mask-RCNN [21] for the detection and segmentation of defects on the surfaces of wood veneers. When it comes to detecting defects on wood surfaces, the proposed method is more accurate and faster than other techniques currently available. However, the segmentation task requires significant amount of time which makes it unsuitable for real-time industrial inspection system. Most of the proposed methods only focused on accuracy and very few methods have improved the efficiency. An improved single shot detector [22] based method was proposed to improve the efficiency of detection. The trained model detects very few types of defects and is limited. A mixed-FCN (Fully Convolutional Neural Network) method was proposed in [23] an improved, fully convolutional network for the detection and recognition of wood defects that outperforms the existing methods while requiring little or no image preprocessing for feature extraction. The model was trained to identify only six different types of wood defects. A fully convolutional network and R-CNN based method [24] was proposed to detect and segment building cracks. The proposed method have limitations due to low performance for real-time application, similarly as in other detection and segmentation methods. An improved CNN based method for weld classification was proposed in [25]. The method uses image convolution to enhance edge features and combines them with integral images in order to create a more accurate segmentation. The algorithm can extract the weld edge and divide the region quickly and accurately while keeping the processing time within real-time requirements.

U-Net a CNN based method with slight modification in its layers by replacing softmax layer with a random forest was proposed in [26] to detect small defects on surfaces. The method is very accurate in detecting small defects. The method is slow and limited to offline setup. A CNN based method was proposed in [27] to segment the defects on standing trees using LIDAR ((Light Detection and Ranging) data. The input data for this method are point cloud data. A mesh is reconstructed from point cloud data. Then reconstructed mesh is used to make relief map and taken as input to U-net for segmentation. The method is computationally expensive and is only suitable for offline applications. To reduce the computation time of CNN, [28] proposed a method that uses nonsubsampled shearlet transform (NSST) to preprocess images. Then images are passed to CNN for detection and classification. The method has an advantage of faster training speed but on the other hand inference is slower.

Other than CNN based deep learning methods, auto-encoder and generative adversarial networks were also used for defect detection. Dual auto-encoders generative adversarial network method [29], a deep learning method was proposed for defect detection in different kinds of products. The GAN (Generative Adversarial Network) has benefit of generating large number of data that can be used for training and which makes the model more accurate for predicting defects on unseen data. This model was trained and evaluated on many datasets that contain different kinds of objects.

III Proposed Method

Network Architecture

In this section we first describe the backbone network MobileNetV3, which is responsible for computing the features. We then describe object detection module i.e. Faster-RCNN, which returns predicted bounding boxes and class label for the detected defects. Figure 1 shows the architecture of our novel method.

MobileNetV3 as Backbone Network

The backbone network or baseline network is responsible for feature extraction. There are many state-of-the-art deep convolutional neural networks such as VGG [14], GoogleNet [15], AlexNet [12] and ResNet [10] which are used as feature extractor or backbone network for object detection. These deep convolutional neural networks focus on accuracy, while having less focus on inference speed. We use MobileNetv3 [30] as backbone network for feature extraction. Unlike traditional deep convolutional neural network, MobileNetV3 is an efficient network architecure and speficifically designed for resource constrained devices.

MobileNetV3 uses depthwise separable convolutions instead of standard convolutions. The standard convolutions operation have spatial dimentions width and height, depth (input channels) and output channels. The standard convoltions have large number of multiplication involved which increases the conputational complexity. On the other hand depthwise separable convolutions, divide the standard convolution into depthwise and 1x1 pointwise convolution. The input and the filters are split into different channels. In depthwise convolution operation, the filters are applied on each input channel separately. For each channels, the corresponding filter is used in the convolution operation. Then a 1 x 1 pointwise convolution is applied to combine the outputs from the depthwise operation. These operations reduce the model size, its parameters and computation time.

For a better classification accuracy, the MobileNetV3 is pre-trained on large scale image dataset i.e. ImageNet [9]. The final 3 layers along with fully connected layers are fine-tuned on our wood defect dataset.

Detection by Faster-RCNN

Faster-RCNN is an object detection algorithm of R-CNN (regional convolutional neural network) family that was originally introduced in [31]. Faster R-CNN [32] is highly accurate detecting very small objects in images. The detector extracts features from different layers of the pre-trained backbone network. Then the features are sent to regional proposal network and region of interest pooling module. The RPN (Region Proposal Network) finds the location of potential object on the input image and ROI (Region of Interest) pooling extracts fixed sized window features and then transfers it to final two fully connected layers for class and bounding box predictions.

For defect detection, MobileNetV3 is pre-trained on ImageNet [9] dataset in a Feature Pyramid Network with Faster-RCNN detector. Then the network fine-tuned on wood defect dataset. The network consists of an input layer, 17 depthwise separable convolution layers with RPN and ROI pooling layers. Features are extracted from many different layers of the MobileNetV3 backbone feature pyramid network. Then Faster-RCNN uses the extracted feature maps from feature pyramid network to predict bounding box location and classes for the defects.

Dataset

The original images for the dataset were provided by a local wood company, where the wood is processed and sold to international markets. We have preprocessed the images and created a dataset. To train our network we needed to create a dataset containing different types of defects classes. Our dataset is divided into multiple splits for training, evaluation and testing purposes. Table 1 shows number of images in each set.

Data Augmentation

The number of original images was insufficient to train our novel deep learning model, which is capable of generalizing well to new, previously unseen data. In order to increase the number of training image samples, we used a technique called data augmentation. The model learns more robust features when it sees slightly modified images created from the original images. The class label remains the same after augmentation. To get additional training data, we used simple geometric transformation functions on images such as shearing, translation, scale, mirror (horizontal and vertical flips), random crop and rotation. These transformations will change the appearance of the images slightly but class label will remain the same. We used Scikit-image and Pytorch library to implement a utility program to do data augmentation. The program iterate through the dataset and take all the images as an input from the training set and then apply the transformations and create multiple images for each of the input and store it in the training folder with the class labels.

Defect Classification

Our dataset consists of 5 different defect classes i.e. knot, wane, edge, stain and branch. Table 1 shows number of images for each of the defect class in each set.

Table 1: Number of images in each split of dataset for different defects

Defect types	Training set	Validation set	Test set
knot	408	51	51
wane	360	45	45
edge	368	46	46
branch	352	44	44
stain	360	45	45

Preprocessing and Generation of Training Data

To train a deep learning model, a large number of labeled images are required. This requires us to manually annotate and label the images. There are many tools available online for annotating images. Labeling images with these tools is time consuming. We have implemented a tool for automatic annotating the images. This tool does the 80% of the job and then a little human effort is required to fix the minor error, which is much less time con-

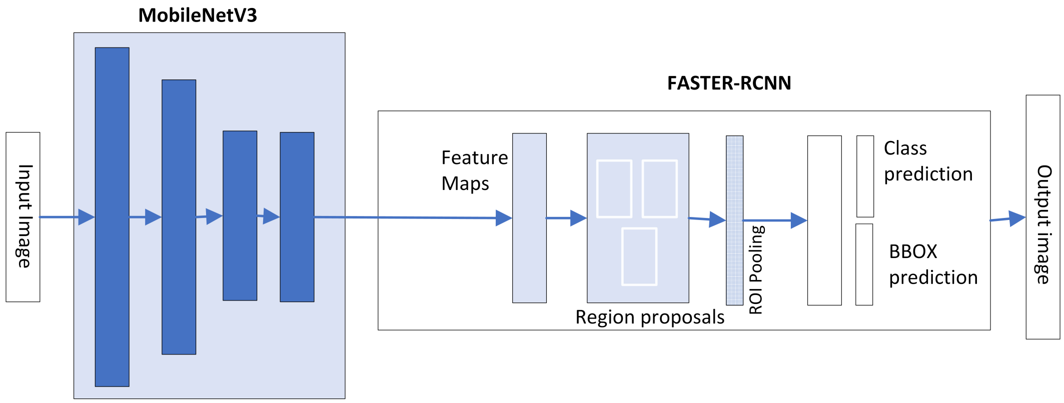

Figure 1. *Architecture of our novel method.*

suming than utilizing the existing tools. This tool outputs a JSON (Javascript Object Notation) file which contains information such as class labels and bounding box size and location of defects in each image. Each file have the same name as the input image file name.

Training

First, we trained the MobilentV3 network with ImageNet [9] dataset and then we used this pre-trained network to fine-tune on our wood defect training dataset. We fine-tuned the network with high resolution images which resulted in better accuracy without affecting the inference time.

IV Results

To evaluate the accuracy of our novel model for defect detection and classification, we used the test set from our dataset, which contains only the images the model have not seen during the training process. We used a unique random color for each unique predicted labels and bounding boxes on our output image. Figure 2 shows the results from our novel method.

Testing and Evaluation

To evaluate the real-time performance of our novel method, we used a wood scanning station with single FLIR Blackfly color camera and LED (Light Emitting Diode) lights. Wood panels with different types of defects were passed into the scanning station with variable speed. The system accurately detected and classified the defects in real-time with an average of 37 frames per second using a GPU based edge device Nvidia Jetson AG Xavier. We have also tested the model accuracy and inference time by using the same device but only with CPU (Central Processing Unit). The average frame rate for detection and classification were 25 frames per second on CPU. We also evaluated our model on single high-resolution images of wood dataset. The top 5 accuracy of our trained model was 99% and inference time on CPU was 0.0112 seconds.

V Conclusion

We proposed a novel end-to-end deep learning network for real-time wood defect detection and classification for industrial quality control and inspection. Our network is constructed by using MobileNetV3 as a backbone network which does the feature extraction. Then Faster-RCNN detector is used to detect and classify regions with defects. Our method have achieved best results by doing real-time defect detection and classification from video feed at an average of 25 frames per second on CPU and average of 37 frames on low memory GPU.

In future research, we will increase the number of images and add more defect types to our labeled dataset. In addition, we will add a segmentation head to the backbone network that will do semantic segmentation of the detected defects.

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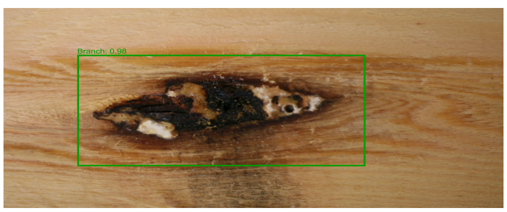
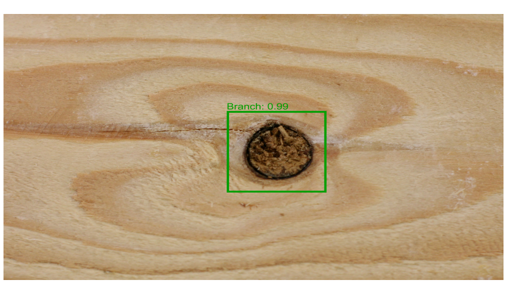
(a) branch and stain

(b) edge



(c) branch

(d) stain



(e) branch

Figure 2. *Detection and classification results on wood defect datasets' test split. Bounding boxes and class labels for each class are shown in their respective color labels. Branch defect is green, edge is red and stain is yellow*

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