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Development of Cross-Cutting Optimizing Scanner for Aspen and Black Alder Boards

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***Abstract*—In the paper, machine learning knowledge is transferred to wood processing industry. A universal Machine Learning system has great potential for the scalability in wood processing industry. In order to increase the yield of high-quality material and reduce the influence of subjective factors in the assessment of the quality of the wood boards, a machine learning model was trained as part of the research. The model was trained on a large set of aspen and black alder board samples, including subjective assessments of the acceptability. This approach ensures that the ML model is able to perceive and standardize different defect compositions that are considered to meet the specified quality requirements. As a result, a more accurate and consistent interpretation of wood defect recognition is achieved, significantly reducing the variation caused by the human factor along with proper feeding mechanism increase the yield of high-quality material. We proved that using ML for wood defect detection allowed to achieve a fully developed and sustainable defect recognition model within 3 months testing period. Identifying wood defects in the production of aspen and black alder boards is both a technologically complex and subjectively influenced process. By combining the assessment of defect intensity, area, structure and location, the model ensures a uniform quality standard throughout production. This reduces unjustified board rejection, improves material utilisation rate and promotes a more stable output of high-quality material**

Keywords— Computer Vision, Deep Machine Learning, defect detection, FPGA, HPC, labelling, quality control, wood processing.

I. Introduction

With forests covering more than 50 % of the country's territory (almost double the world average), Latvia is 5th of the most forested EU member states and 2nd greenest country. Over the last 80 years, the forested area has doubled while standing volume has increased 3.8 times, reaching industrial production 11 550 thousands of cubic meters in 2024 with 4 730 for export. The forestry industry has always been Latvia's export leader [1]. Wood and its products are the most significant export sector, comprising around 50% of total export value [2].

In recent years, computer vision techniques for defect detection have been widely studied. The evaluation of wood quality is a sophisticated and diverse process that demands meticulous observation and classification of a broad spectrum of physical characteristics, especially density, and humidity properties [3]. Machine Learning approaches, nowadays offer considerable improvements by integrating multiple models to recognize and interpret complex patterns in large datasets [4]. The development of image-based wood analysis has shown significant progress over the past decade, evolving from simple texture recognition to advanced predictive modelling systems [5]. Forestry industries have shifted to more sophisticated frameworks of deep learning architectures. Modern technologies have developed ensemble frameworks that combine multiple CNNs [6], this advancements achieved high classification accuracy across various wood species datasets. Although previous research shows that individual machine learning models can effectively predict wood properties like density and moisture content, however, these models operate independently, which may limit their ability to fully capture the complex, non-linear relationships inherent in wood properties [3].

The Computer Vision system along with Machine Learning became state of the art in the wood defect detection (knots, shakes, checks, wane, pattern defects, also many geometrical anomalies like cupped, twisted bowed or crooked timber). It provides necessary quality control regarding the processing of wood products, so the

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optimisation of sawing processes in the wood industry is critical for maximizing efficiency and profitability. Sawing optimisation is the process of maximizing the yield of wooden products from a board by cutting the board into the optimal size and shape. By optimizing the sawing process, the wood industry can reduce the amount of waste, which helps to conserve natural resources and reduce environmental impact. Additionally, sawing optimisation helps to improve the quality of wooden products and expand their utility for a wider range of applications. [7], [8].

In practice, for board production, customers often demand a wide range of board sizes, so sawing optimisation problem is also very important for wood processing companies [9], [10], [11], [12].

However, output of extraction processes is difficult and complex, particularly for wood products with high quality requirements [3], [13]. Wood defect detection is difficult because every piece of wood has a unique appearance and may have multiple feature characteristics within a single piece. Hence, a method that can learn wood features automatically instead of complex extractions is needed [14], [15].

As a result, a defect detection is used with a deep convolutional neural network (DCNN) allowing to interpret any defects. The development of a deep machine learning detection systems is contributing to technological innovation of wood industry [16]. Usage of the DCNN for defect detection also requires correct selection of methods and equipment due to the high variability of natural defects such as knots, cracks, etc., which makes it very challenging to introduce the best type of DCNN method for board evaluation. Professional scanners feature integrated designs, high precision, and factory-calibrated systems, ensuring consistent, high-resolution outputs with minimal user intervention. However, their high cost and proprietary software limit accessibility [17]. Another aspect of wood defect detection lies in sustainability efficiency in promoting a sustainable future by its renewable properties and carbon sequestration capabilities [18], [19].

The aim of this research is to synthesize recent research on emerging wood defect detection technologies that enhance output quality and increase speed. This research is presenting applied findings in development of cross-cutting (transverse) optimizing scanner for aspen and black alder boards with AI-driven quality control and circular economy integration within wood processing industries

II. Specifications of Wood Processing Environment.

For wood processing companies, we have developed prototype with advanced scanners that not only detect defects in products, but also offer the most optimal solution for obtaining maximum value from each product through management and software interface (UI), as well as ensure autonomous operation of the product line. The company's scanner captures board images and topographic images from both sides (with 4 triangulation and 4 visual cameras and a translation system for optical alignment), obtaining complete information about each board/log. Next, the artificial intelligence algorithm divides the boards into segments with good and defective wood areas through digital labelling. This data goes through an optimisation algorithm that divides each board into a predefined range of products and already places the blades of the next circular saw according to our algorithm data. A vision system was developed for wood processing conveyer line (Fig. 1)

Fig. 1. Cross-cutting optimizing scanner for cross-cutting and quality (*source: company LV Timber SIA data*).

Previously, in one of the key production processes – cross-cutting or lengthening, marking was done manually, with the operator marking the wood defects with a crayon. This assessment is influenced by the operator's skills, level of well-being, including mood, fatigue and other factors affecting human decision-making (human factor). Often, under the influence of these conditions, product defects are not evaluated effectively, and properly enough and high-quality material is "lost" or used inefficiently. This process now is improved and digitized by introducing modern four-sided scanning technology into the production process, thus, using modern scanning technologies, obtaining the optimisation result digitally and transferring it to the optimisation sawing machine. Scanning technology, together with its mechanisation, makes the cross-cutting results more efficient, more stable, and more accurate, removing the main responsibility for deciding the outcome from the operator, as well as making the operator's work physically easier.

One of the key processes in the development of this scanner was the creation of a reliable neural network for wood defect recognition as well as positioning and feed tractor efficiency. The whole labelling process would not be possible without one important tool: board automatic fixing and feeding mechanism at the scanner (Fig.2).

Fig. 2. Board fixing and feeding mechanism (*Source: authors created based on SIA LV Timber data).*

With the current solution it is possible to adjust following board dimensions 19/32x100/135/155x1800-3000 mm. During test period from August 2025 to October 2025, sawing a total of 6490 m3 of aspen saw logs, a reference yield of 966.65 m3 or 14.89% of high-value products were obtained during this period. In comparison, the application of the new optimisation scanner in 2026 has increased yield by 0.50 percentage points, to 15.39%.

III. Quality Control Requirements

The Machine Learning model was trained on a large sample set of aspen and black alder boards, including subjective assessments of the acceptability of the color by various operators for both white and heat-treated products. This approach ensures that the ML model is able to perceive (e.g. moisture levels) and standardize different color compositions that are considered to meet the high quality requirements. The result is a more accurate and consistent recognition of wood color, significantly reducing the quality variation output caused by the human factor and increasing the yield of high-quality material. It is important to indicate both the properties of the actual defect and the effect of false recognition on the wood boards. This is especially useful in situations where there are uncertain situations, and it is difficult to determine the difference and boundary between defects. For example, for aspen boards, the differences between the paint and the wood rots are very difficult to see for the untrained eye based on the image alone (e.g. Fig. 3).

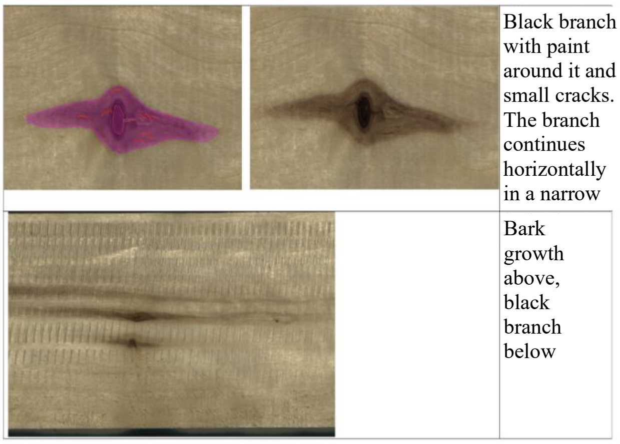

Fig. 3. Example of defect labelling (*Source: authors created based on SIA LV Timber data*).

In life, this difference is easier to see based not only on the colour of the defect, but also on the reflection in different light, the texture and moisture of the wood. By applying topography, the true nature of the wood defect is revealed, and we achieve more reliable labels. Two categories for quality groups were created, which are especially important for sustainability and product segments where quality is not critical.

Quality criteria define the types of defects and errors based on wood species. Defects are divided into categories that are confirmed and clearly visible, whether the defect has been confirmed but its boundaries are not permanently identifiable, or whether the defect has not been confirmed. Next, the labeller must be able to mark all defects visible on the timber according to the standards specified in the criteria. Each labelled defect is assessed in the context of error categories, where they fall into 2 categories: *Category 1* - These defects are not used in any of the products to be optimized and are therefore considered to be the most critical (e.g. any wood rots [Butt, White, Sapwood, Carbonized wood, etc). *Category 2* - These defects are allowed in some of the products, so their use is allowed later: e.g. Branch, Bark, Colour, Core, Crack. As a result, 17 defect classes were elaborated to promote sustainability and quality recognition. The introduction of the new sorting approach significantly reduces the generation of waste material during the lengthening process and allows to increase the volume of finished high-value material by 0.5% of the sawn logs, achieving a total yield exceeding 15.39%. The selling price of top grade high-value products has been on average 1050 EUR/m3 over the past year.

IV. Solution and Results

During testing period if any of these defects are not found in the image, then the optimisation algorithm ignores it and possibly places the saw blades in a less optimal or incorrect way.

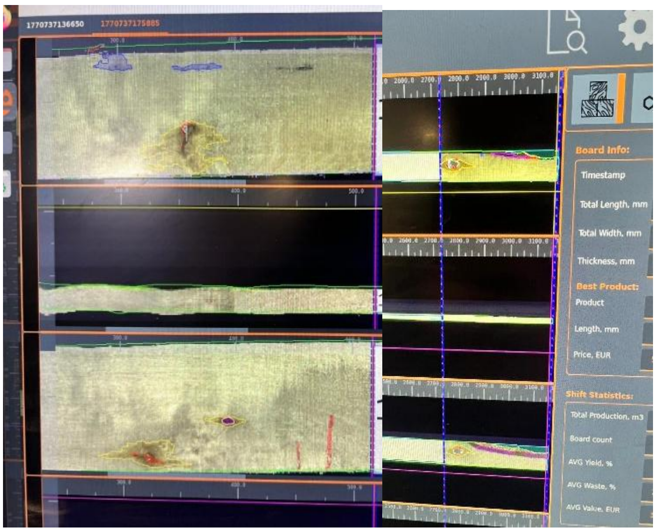

Fig. 4. Example of results of ML model tests and images with real collected samples (*Source: authors created based on SIA LV Timber data*).

As a result ,ML recognition efficiency plays a vital role for final result. The labelling application also has various functional tools such as hiding other defects to facilitate labels. A total of 1411 full board image samples were scanned for labeling, ML development, and ML verification (Figure 4). It should be noted here that this is a special panel available to managers with cost optimisation. The labelling process manager also has access to the overall panel view, which shows the total annotations made by the system, the ability to assign more boards and calculate the total number of defects in them (Figure 5).

This is a very important step that determines the total value of the order and supply material utilisation at the end of the month. Based on the existing problems regarding the determination of wood quality which is closely related to wood defects, the role of technology is needed to help identify wood defects. Results achieved within the framework of the activity: design solution documents developed; software operator interface built for scanner prototype tests; defect identification tested in real samples, 17 defect classes separated, defect descriptions developed and annotations prepared; 1400+ boards scanned for sample marking, MI development and MI verification; scanner prototype manufactured and installed in the Cross-Saw Department.

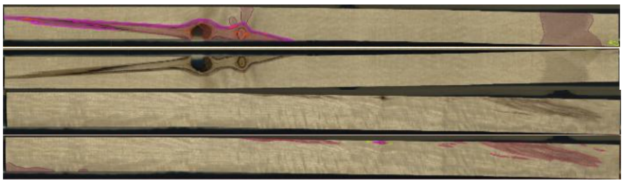

Fig. 5. Example of UI for board cutting optimisation and cost (*Source: authors created based on SIA LV Timber data*).

In addition to wood defects such as branches and cracks (identification of which is primarily necessary for various coniferous wood production companies), it is very important for aspen and black alder wood to be able to digitally correctly and accurately assess defects such as wood coloration in the production of specific products. It was important to recognize, categorize and transfer the information from scanner to the saw in real time in the development of the prototype of the scanner technology; processing speeds of over 60 meters per minute were required. First of all, the optimisation model needed to create a certain degree of "freedom" for board sorting, allowing for a controlled reduction of product quality requirements under certain conditions, based on the intensity, area, difference from the base tone and location of the coloration. Identifying coloration defects in the production of aspen and black alder lumber is both a technologically complex and subjectively influenced process. The ML model developed in the study significantly improves this process, as it is able to learn the operators' subjective perceptions of which color combinations are acceptable for different product types.

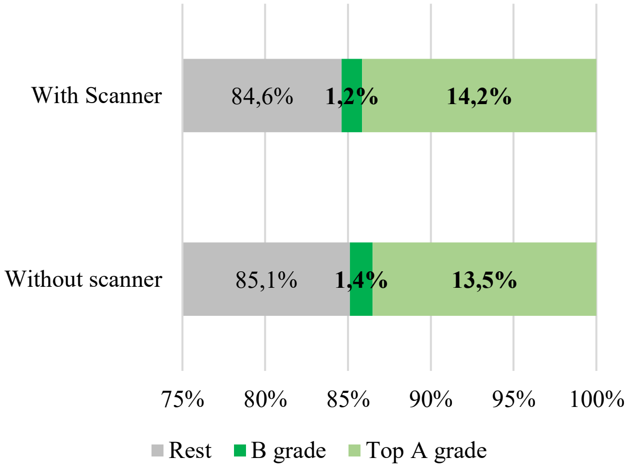

Fig. 6. Efficiency results after testing period (*Source: authors created based on SIA LV Timber data*).

The company's efficiency is positively affected by the fact that the cross-cutting optimisation scanner is able to objectively and sustainably determine the difference between high-quality materials of class "A" and class "B". Currently, the average selling price of class A products is 30% higher. As well as material with lower quality is ensuring more sustainable production (Figure 6).

TABLE I. ML OPTIMIZING SCANNER EFFICIENCY RESULTS

0,50%	Increase in the yield of high-value material, % of sawn logs
15,39%	The useful yield of high-value material against sawn logs, calculated as 14.89% + 0.50%
8%	The effect of the optimisation scanner's defect recognition and sorting. The useful yield of "B" grade is reduced to 8% of the high-value materials obtained in the production process (in the inventory tests, employees marked an average of 9.76% of the high-value products as grade B, but the scanner - eight percent); accordingly, a larger proportion of high-value materials is marked as grade A and is sold more expensive
1,76%	Reduction in "B" or lower-grade high-value material, % of the total amount of high-value material obtained, calculated as 9.76% - 8%

Prior to the new scanner development initiative, the company's employees (operators) visually evaluated each board of high-quality material and sorted them into class A and B. The grades are determined based on the area, intensity, and uniformity of the coloring. Data from August-October 2025 show that 9.76% of high-quality materials were indicated as class B materials. Trials of the new technology show that employees have so far subjectively determined class B for material that objectively meets the parameters of class A in too many cases. The use of the new optimisation scanner technology reduces the proportion of class B to 8.0%. Both quality criteria and quality standards are used in the labelling evaluation process to make a final decision on the accuracy of the labels based on board quality requirements (Table 1).

Based on the necessary quality standards, it was possibletran to scale our solution for other wood processing applications. Using our solution as a guide, a methodology of quality criteria and standards, it is possible to quickly elaborate high-precision ML markers with ability to improve efficiency during longer period of testing. The ML Digital Labelling model integrated with a fully automated sawing cycle allows the plant to work with different scenarios of size, wood quality and production capacity. Our system is currently allowing to identify and process up to 2500 m3 of aspen saw logs per month, with scalability potential. It is necessary to mention that our system could be potentially used on much faster processing lines, and with different board sizes.

Conclusions

This paper explored the scalability of Machine Learning technologies for wood surface defect detection with an integration to industrial application. Based on the framework created from the project it is possible to reduce labor costs within the visual inspection and increase efficiency compared to manual and automated conventional optical systems. Compared to conventional manual approach with human factor issues, our system is giving possibility to quickly (in 60 m/minute production lines) identify multiple features and defects, and generate optimisation (cross-cutting) instructions considering 17 defect groups of classes.

Results achieved within the research framework of the testing activity: industrial application solution documents developed; software operator interface built for scanner; defect identification tested in real samples, 17 defect classes separated, defect descriptions developed and annotations prepared. Wood defect detection and sawing optimisation process can be improved and digitized by introducing modern four-sided scanning technology into the production process. The application of modern ML scanning technologies in obtaining the optimisation result digitally and transferring it to the optimisation sawing machine is confirmed. Scanning technology, together with its mechanisation and integration to industrial application, makes cross-cutting results more efficient, more stable, more accurate, as well as making the operator's work physically easier.

Therefore, we proved that quality control system developed for the wood processing industry can be scaled up in size and quality. The result is a more accurate and consistent interpretation of wood colour, significantly reducing human-induced variation and increasing the yield of high-quality material. The company's efficiency is positively affected by the fact that the cross-cutting optimisation scanner is reliable in wood defect detection and is able to identify the difference between high-quality grade materials of class “A” and “B”. Currently, the grades are determined based on the area, intensity, and uniformity of the colouring allowing to increase selling price by 30% (when a board is correctly identified as class “A” as opposed to class “B”) due to more precise recognition and positioning for processing. During testing period, it was confirmed that the use of the new optimisation scanner technology reduces the proportion of class B grade to 8.0%. The final result of the research paper is a successfully developed prototype of an aspen and black alder cross-cutting optimizing scanner, which is capable of fully functioning in a production environment with aligned testing period (both mechanically and digitally), which is able to ensure modern automated operation requirements and tasks.

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