Improving Supervised Machine Learning Models in Forest Industry with Generated Data

Dag Björnberg[1,2], Morgan Ericsson[2], Johan Lindeberg[2], Welf Löwe[2] and Jonas Nordqvist[2]

***Abstract*— The industry sector's need for automated models used in production is rapidly increasing. However, obtaining useful training data can often be time-consuming and costly. In this extended abstract, we propose the idea of generating labeled data that can be used to train supervised machine learning models to be used within the forest industry and discuss some use cases in which these datasets can be applied.**

I. Introduction and Problem Statement

The forest industry has many use cases where automated models are desirable to obtain. Tasks of interest can range from image recognition through the production chain to quality assessments. By recognizing the log throughout the process, traceability is created, allowing for better workflow optimization and preventing illegal logging. In addition, automatic log quality assessments can be used to quickly classify the quality of logs, replacing manual effort.

For these tasks, machine learning models can be applied, which, provided with labeled training data, *i.e.*, images with known properties, show high accuracy. However, obtaining such labeled training data can be expensive, since it an often difficult task that requires a lot of manual effort. This is very often the case in the forest industry. Recognizing log-ends through the production chain requires a lot of manual work with collecting matches. In wood quality-related assessment tasks, such as tree ring counting or tree ring detection, the amount of manual effort needed to label data is vast. For this reason, we investigate how generated training data can be utilized in supervised machine learning models to improve performance or when real data are too expensive to obtain.

The extended abstract displays two use cases on which we apply supervised machine learning models trained on generated data, and discusses possible future use cases where generated training data could be helpful.

II. Use Cases

Evaluation of the impact of generated training data used in supervised machine learning models is here demonstrated using two cases: image recognition of log ends and image quality assessments of log ends. For image recognition, we demonstrate how a so-called *cGAN-augmenter* can be used to enhance standard augmentation techniques. For image quality assessments, we demonstrate how generated labeled training data can be used to improve the performance of two machine learning tasks: estimation of pith location and tree ring counting. The generated data are constructed using different variants of *Generative Adversarial Networks* [1].

A. Image recognition

For image recognition of log ends, an algorithm based on the so-called *triplet loss* [2] was developed to recognize log ends between two different stations in a sawmill environment. A *triplet* consists of an *anchor*, a *positive* and a *negative*. The anchor and the positive are different images of the same individual, while the negative is a different individual. The triplet loss encourages to minimize the distance between the anchor and the positive and to maximize the distance between the anchor and the negative. In this way, our model can learn to map an image from one station in the sawmill to another. However, collecting triplets is a time-consuming task that requires searching through a database to either verify that a match is correct or to find the correct match among the top matches. To avoid this procedure, one idea would be to, instead of searching the database to find the matches, use standard augmentation techniques to create a positive from an anchor image. However, with such a method, it can be difficult to capture some of the realistic perturbations that can occur in a log end as time passes, where drying cracks may be the most evident example. For this reason, we propose what we call a *cGAN-augmenter*, in which we can add realistic perturbations, thus creating more difficult positives compared to standard augmentation techniques.

The cGAN-augmenter is based on *conditional Generative Adversarial Networks* (cGANs) [3], using an edge map as an input image. The cGAN then learns to transform this edge map into a realistic-looking log end, maintaining the properties presented in the edge map. Since interesting features such as cracks are presented in the edge map, we may add perturbations such as synthetic cracks to the original image, take its corresponding edge map, and then generate a new image with realistic-looking features added to it. In this way, we can create more hard positives that are useful when training the model.

B. Quality Assessments of Log Ends

Multiple quality measurements of wood can be estimated from the log cross-section. In a paper, currently under review, we investigate estimation of various such measurements. One measure to consider is pith location, which serves as a point of reference to determine other properties of the cross-section [4]. One such important property is tree ring width [5], [6], in which knowing the location of the pith is

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[1] Softwerk AB
[2] Linnæus University

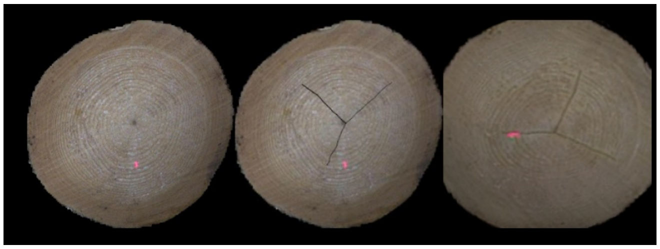

Fig. 1. Description of our proposed cGAN-augmentation. Some additional features are added to the original image, in this case cracks originating from the estimated pith location. These simple additional features are then translated into photo-realistic looking features in the augmented image.

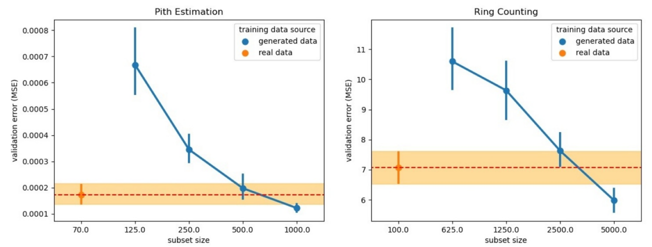

Fig. 2. Comparison of performance using real training data and generated training data for two different tasks; pith estimation (to the left) and tree ring counting (to the right). Performance is measured in terms of the lowest validation error on real data. The bars represent the 95% confidence intervals.

a prerequisite. For these reasons, tasks such as estimation of pith location and tree ring counting are interesting. However, labeling such properties is very time-consuming and can also be subject to misjudgments.

We examine the possibility of using generated training data with controlled properties. The research question behind this is whether supervised machine learning models trained on artificial data can outperform models trained on smaller sets of manually labeled real data, at least in the researched analysis tasks.

We use another method based on Generative Adversarial Networks, where we use a *CycleGAN* [7] to convert a drawing with controlled properties to a fake edge map. This fake edge map is then passed through a cGAN to obtain a photo-realistic image, maintaining the properties present in the drawing, which we can have complete control over. We use our approach to generate two distinct datasets: one of entire log ends and one of patches of log ends. We use these generated datasets to train two machine learning models, one for estimating the pith location on entire log ends and the other for counting tree rings on patches. We compare the performance of our models against baseline models that are trained on smaller sets of real data. The baseline models are obtained using transfer learning and various augmentation techniques are used to avoid overfitting. Then we use the same settings, only changing the training dataset source, *i.e.* replacing real training data with generated training data. The results show that both the estimation of pith location and tree ring counting can be improved by replacing the real training data with larger sets of generated training data.

III. Discussion and Future Work

We provide two methods with similar ideas to either enhance standard augmentation techniques or generate completely new images with controlled properties.

For the augmentation technique, we discuss how to add realistic perturbations to images of log ends. This can be useful for image recognition of log ends since the log end might have some added features over time. The most evident example is drying cracks, but one can also think of other added perturbations such as snow, dirt, or spray color. For example, our augmentation method could potentially be useful for object detection of cracks or knots. For these cases, we can add such features to the original image at a controlled location, avoiding manual labeling.

For the completely new images, we provide two proofs of concept to answer our research question. In both cases, we see that the models trained on generated data outperform those trained on real data. However, this comes at the cost of needing more training data. On the other hand, we can completely avoid manual labeling, which can be useful for the two tasks presented here and other related tasks such as tree ring detection, where manual labeling is very time-consuming.

Exploring other generative models for these different tasks would be of further interest. As an alternative to our cGAN-augmenter, we could explore the possibility of using *Variational Autoencoders* [8] or *Flow-based Generative Models* [9]. These methods allow for modeling of complex data distributions to simpler latent space representations, which could allow for more variation in the augmented images.

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