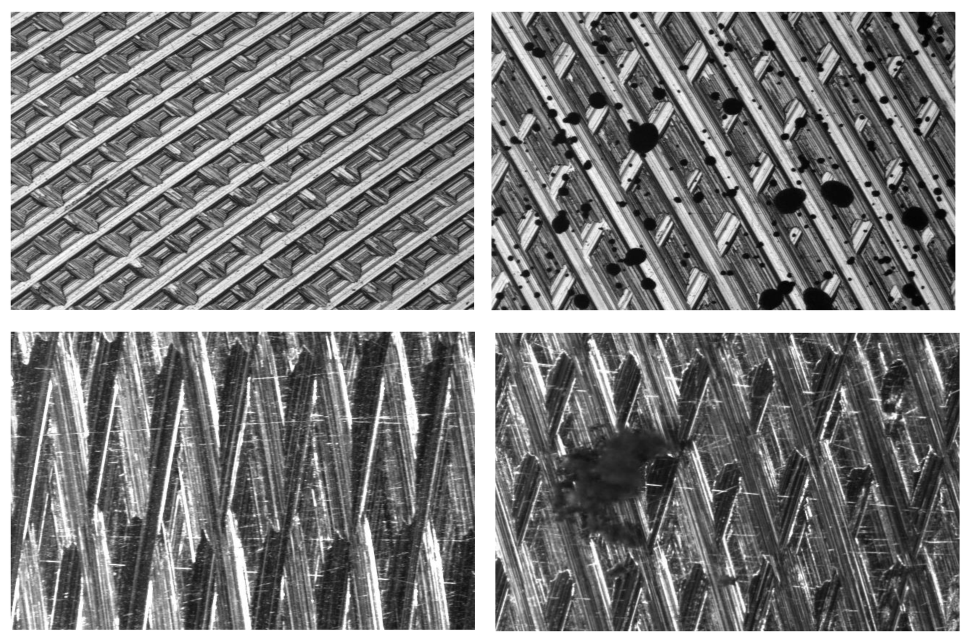
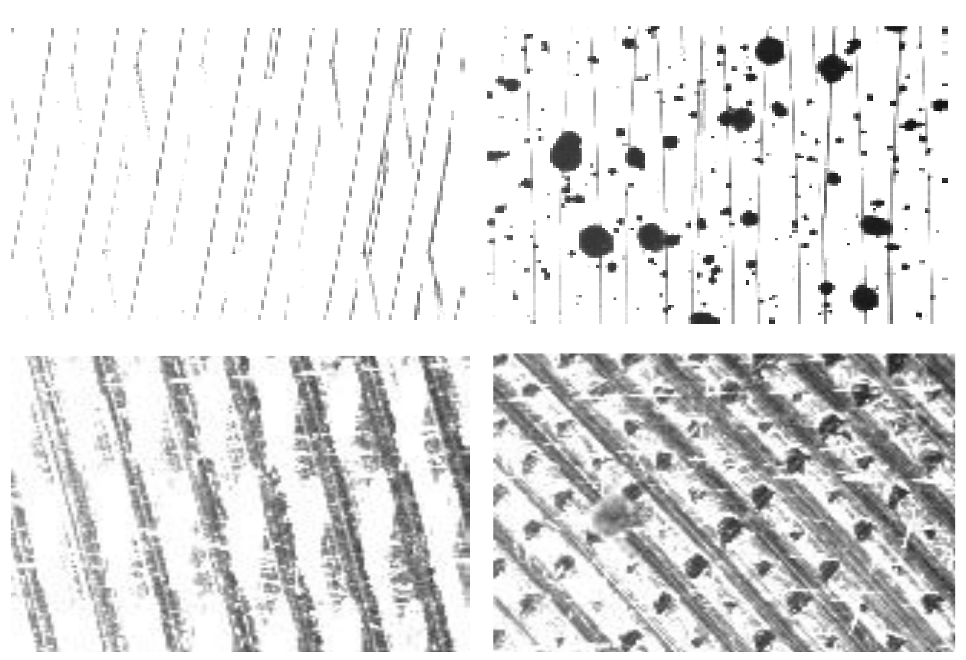
Identifying Aluminum Manufacturing Defects with Naïve Bayes Classifiers and Neural Network Classifiers

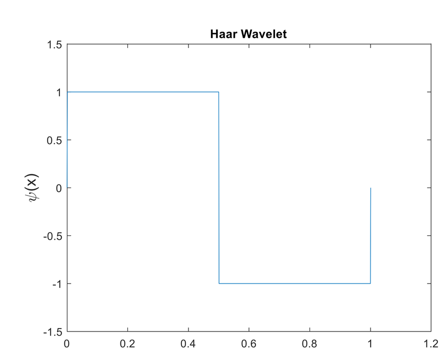
Author: Ashley Batchelor, U.W. Physics M.S. Student (aibatchelor22@gmail.com)

Abstract: In order to investigate techniques for using machine learning with machine vision inspection, Naïve Bayes Classifier models and Neural Network Classifier models were used to identify two types of simulated manufacturing defects on aluminum workpieces. This work investigated various methods of pre-processing images, and various neural network training parameters to improve defect identification accuracy.

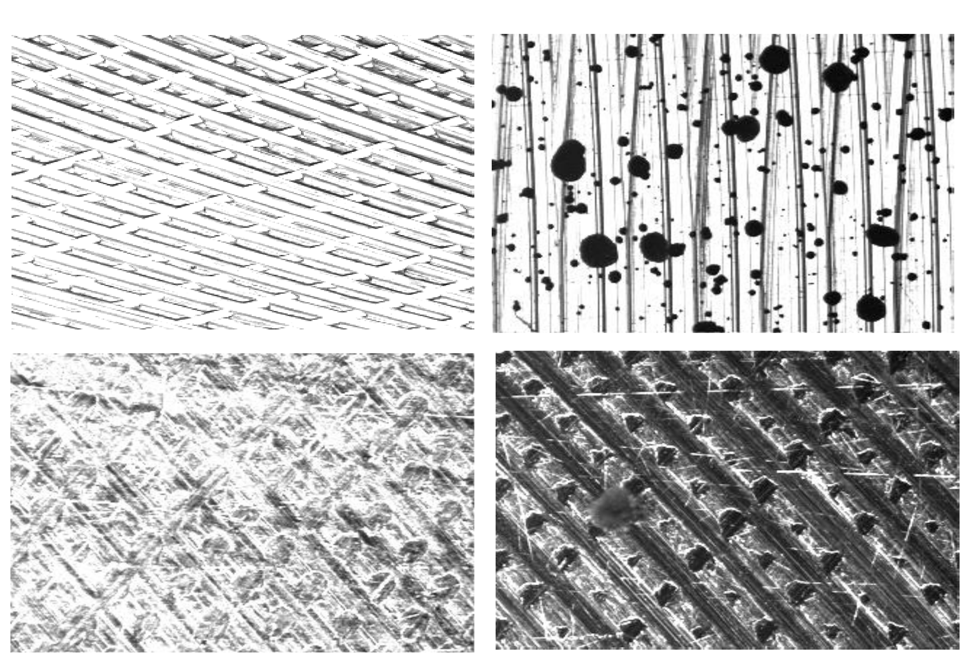


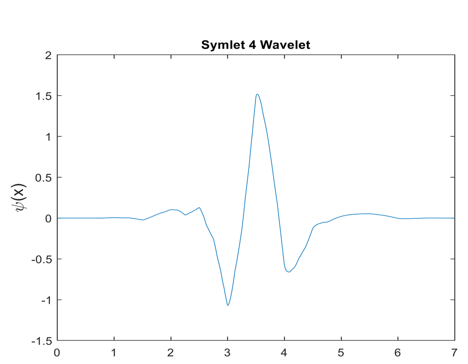
Raw Images - Machined aluminum workpiece with no defect, machined aluminum with spray painted simulated defect, machined aluminum workpiece with no defect, machined aluminum with graphite simulated defect.





Haar Transformed Approximation Coefficient Images - Machined aluminum workpiece with no defect, machined aluminum with spray painted simulated defect, machined aluminum workpiece with no defect, machined aluminum with graphite simulated defect.





Symlet 4 Transformed Approximation Coefficient Images - Machined aluminum workpiece with no defect, machined aluminum with spray painted simulated defect, machined aluminum workpiece with no defect, machined aluminum with graphite simulated defect.

Mitutoyo QVStream Machine Vision Inspection System

Methods

A first type of defect was simulated with black spray paint droplets, and a second type of defect was simulated by passing graphite powder through a screen. The workpieces were prepared and imaged with a Mitutoyo QVSTREAM machine vision inspection system at Micro Encoder, Inc.

For each set of images, I trained a Naïve Bayes model based on several preliminary treatments of the images. These treatments included raw images, second level Haar wavelet transformed images (only approximation coefficients), and first level Symlet 4 wavelet transformed images (including approximation coefficients, horizontal detail coefficients, vertical detail coefficients, and diagonal detail coefficients). I trained a Naïve Bayes model using training data that included both types of defects labeled as "defective" or "non-defective," and using training data that included both types of defects labeled as "type 1 defective," "type 2 defective," or "non-defective."

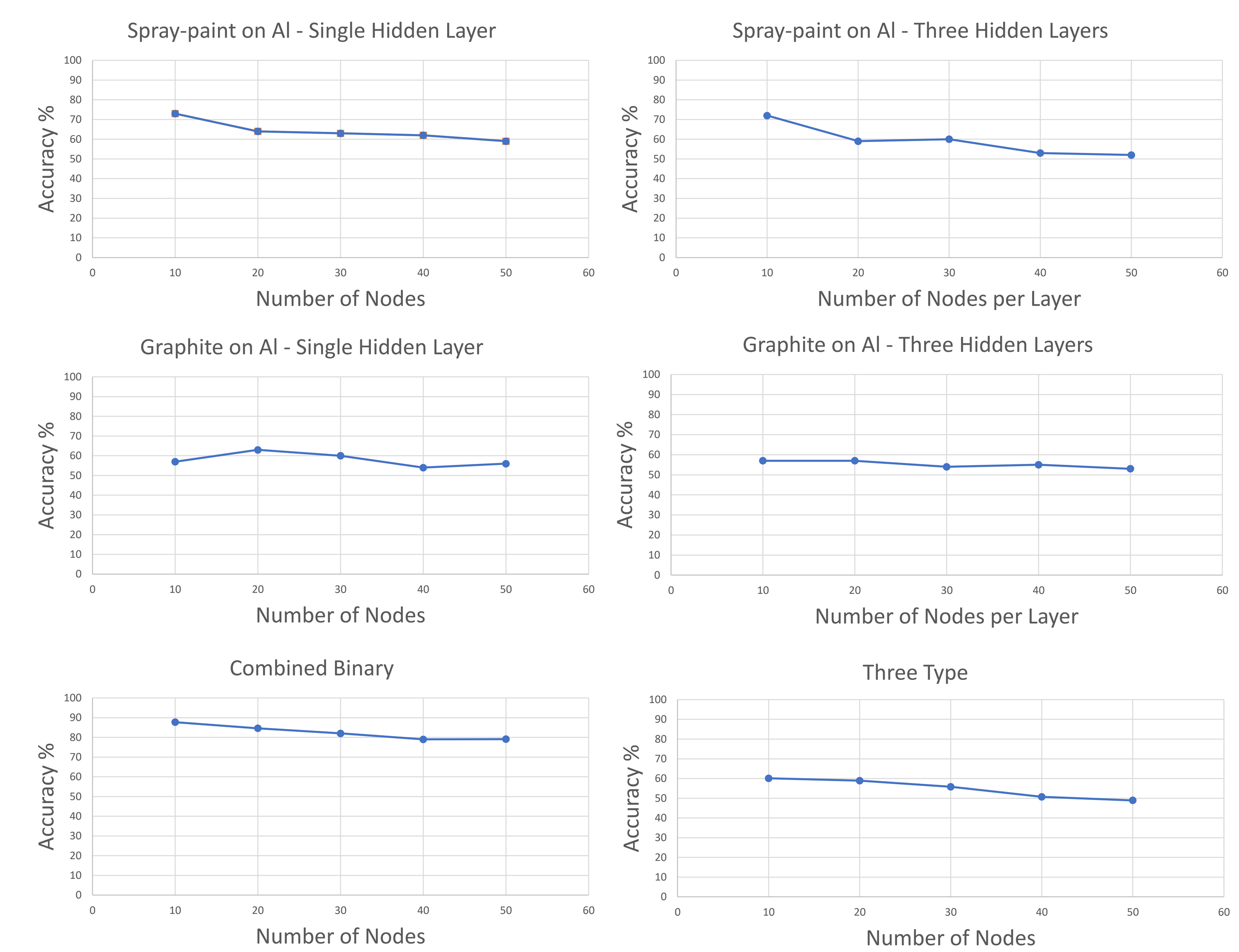
To compare machine learning techniques, I trained models using neural network classifiers trained on raw images for each type of defect individually, for combined defects labeled "defective" or "non-defective" (combined binary), and for both types of defects (three type) labeled as "type 1 defective," "type 2 defective," or "non-defective." For the binary classifications I trained the networks with a simple single layer with different numbers of nodes, as well as a three layer network with a log-sigmoid transfer function, a linear transfer function, and a radial basis transfer function. I only used a single layer for the combined binary and the three type since the three layer did not give any significant advantage when I tested the individual defect models.

I cross validated each method by training a new model 20 times (with the same parameters) and calculated the overall average accuracy over the 20 trials.

Computational Results

	Spray-paint on Al	Graphite on Al	Combined Binary	Combined Three Class
Raw	91.8%	57.5%	49.5%	49.2%
Haar	90.8%	61.3%	61.8%	49.7%
Sym-4	59.3%	95.0%	68.0%	67.0%

Accuracy of Naïve Bayes Methods



Accuracy of Neural Network Methods

Conclusions

Naïve Bayes models generally gave more accurate results than neural networks for single types of defects, but neural network models gave more accurate results when for classification including both types of defects. Raw images with a Naïve Bayes model gave the best results for binary classification of the spray-paint defects (91.8%), whereas Symlet-4 transformed images with a Naïve Bayes model gave the best results for binary classification of the graphite defects (95.0%). For binary classification including images of both types of defects, a neural network model gave the best results (87.7%). For three type classification including images of both types of defects, a Naïve Bayes model with Symlet-4 transformed images gave the best results (67.0%).

Acknowledgements

The image data used for this work is a proprietary data set prepared by Micro Encoder, Inc., which is not available to the public. All analysis of the data described herein is my own.

References

US Patent Number 8,315,453 "Defect classification with optimized purity" (Applied Materials Israel Ltd.)
US Patent Number 8,660,340 "Defect classification method and apparatus, and defect inspection apparatus" (Hitachi High Technologies Corp.)
US Patent Application Number 20160163035 "Automatic Defect Classification Without Sampling and Feature Selection" (KLA-Tencor Corp.)
Karras, D.A "Robust Defect Detection Using Improved Higher Order Wavelet Descriptors and Support Vector Machines for Visual Inspection Systems" Proceedings of the 2006 IEEE International Workshop on Imagining Systems and Techniques (IST 2006), 2006, pp.180-185
Kutz, J. Nathan. Data-Driven Modeling & Scientific Computation: Methods for Complex Systems & Big Data, Oxford University Press, 2018
Shumin, Ding & Zhoufeng, Liu & Li, Chunlei. (2011). "AdaBoost learning for fabric defect detection based on HOG and SVM." International Conference on Multimedia Technology (ICMT).
Tao, Xian, et al. "Automatic Metallic Surface Defect Detection and Recognition with Convolutional Neural Networks." Appl. Sci. 2018, 8, 1575.
Zhang, Harry. (2004). "The Optimality of Naive Bayes." Proceedings of the Seventeenth International Florida Artificial Intelligence Research Society Conference, FLAIRS 2004. 2.