Enhancing Alloy Microstructures and Deformation Process Efficiency via High Volume Surface Imaging and Convolutional Neural Network Analysis

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Abstract The efficiency of manufacturing of engineered products from wrought alloys significantly impacts our environment, global energy use, and direct production costs. Shaping of alloys via deformation to fabricate metal products accounted for 4% of the energy used in all manufacturing in the USA and in China in 2013 [1]. A large portion of this energy is lost due to material yield losses. For example, yield losses amount to 44% of the sheet metal used in automobile production [2]. For some specialty alloys, entire heats of metal can be unformable, resulting in 100% scrap or the need for 100% recycle. Our research demonstrates a data-driven approach to enhance the efficiency of deformation processing and achieve more consistent microstructures and properties.

First, applying machine learning to metal deformation processing requires having large amounts of data. Unfortunately, traditional methods of measuring microstructures (e.g. electron microscopy) and properties (e.g., tensile testing) are not conducive to creating large data sets. Thus, a critical need is to establish methods to measure and compile microstructure and properties data to correlate with desirable and undesirable manufacturing outcomes. Towards this end, optical microscopy of surfaces can be automated and inexpensively applied to quantify the effects of deformation on microstructures. For wrought products made from low stacking fault energy alloys such as stainless steel, slip bands and twins are readily apparent on their surfaces and can be analyzed to determine grain size distributions, grain orientation distributions, and the degree of deformation homogeneity. Localized imperfections such as inclusions, voids, or cracks can also be detected and integrated in machine learning models with other properties and attributes of surface images.

This study focuses on assessing the predictability of deep drawing of austenitic stainless steel sheet. We first developed a method to approximate the crystallographic textures present in the sheet via surface slip band trace analysis to identify the area fractions of grains oriented for excessive thinning during deep drawing. Grains associated with Brass, Goss, Rotated-Goss, and Copper textures were identified. Then we automated data collection using an Olympus LEXT OLS5100 3D Laser Confocal Microscope. We collected and curated over two thousand 256 µm x 256 µm micrographs as input to the machine learning model. An example input image is shown in Figure 1. Each micrograph provided at least 100 grains for analysis. For such image-intensive data, we selected and trained a deep Convolutional Neural Network (CNN) coded in Python using the TENSORFLOW library. A series of convolutions, nonlinear activations using the Rectified Linear Unit (ReLU) function, and pooling layers was used to learn non-linear representations hidden within the input data, while a final multilayer perceptron was implemented for the output layer of the model. The model was trained using the Adam optimizer to minimize the Binary Cross-Entropy loss function.

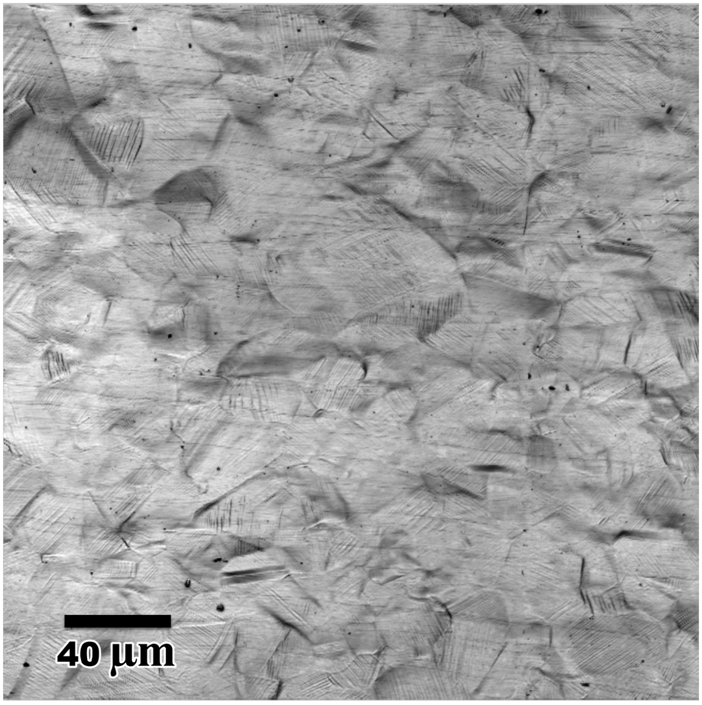

Figure 1 *– Laser confocal micrograph of stretched stainless steel surface to train the CNN model*

The CNN model was trained and then validated against two sets of randomly sampled micrographs of formable and unformable sheet. The CNN model distinguished formable and unformable sheet with 92% accuracy. With this surprisingly accurate result, we are investigating the model to understand the features that were key to the successful classifications. We are also evolving the model to analyze additional alloys.

References

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